Forecasting Demand for KC-135 Sorties: Deploy to Dwell Impacts

GRADUATE RESEARCH PAPER

Theodore A. Langstroth IV, Major, USAF

AFIT-ENS-GRP-13-J-5

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

The views expressed in this thesis are those of the author and do not reflect the official policy or position of the United States Air Force, Department of Defense, or the United States Government.

AFIT-ENS-GRP-13-J-5

**FORECASTING DEMAND FOR KC-135 SORTIES: DEPLOY TO DWELL
IMPACTS**

GRADUATE RESEARCH PAPER

Presented to the Faculty

Department of Operational Sciences

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the

Degree of Master of Science in Logistics

Theodore A. Langstroth IV, MA

Major, USAF

June 2013

FORECASTING DEMAND FOR KC-135 SORTIES: DEPLOY TO DWELL IMPACTS

Theodore A. Langstroth IV, MA
Major, USAF

Approved:

_____   _____
Bradley E. Anderson, Lt Col, USAF (Advisor)   Date

AFIT-ENS-GRP-13-J-5

Abstract

The KC-135 aircrew deploy to dwell ratio is currently 1:1.3, well above the Air Mobility Command goal of 1:3. On average, a KC-135 aircrew member is away from home station nearly six months of every year. While undoubtedly a quality of life issue, the deploy to dwell ratio may be an indicator of more serious problems. Research indicates sustained high operations tempo can have a negative impact on flying safety, aircrew retention, and even physical or mental health.

This research applies time series forecasting techniques to KC-135 sortie data from operations in Iraq, Afghanistan, and CONUS missions. These forecasts identify trends for use in predicting future changes to the deploy to dwell ratio. Data from the Iraq drawdown are used to develop an analogy for a similar drawdown in Afghanistan projected for 2014. Aggregate data are analyzed for overall trends. The three year moving average of KC-135 sorties indicates a downward trend in sortie demand, but with marginal statistical confidence. The analysis suggests the KC-135 deploy to dwell ratio will improve, but does not positively quantify that improvement. In a best case scenario, active duty KC-135 aircrew deploy to dwell ratio could improve to 1:1.7 with the end of OEF.

Acknowledgments

I would like to thank my advisor, Lt Col Brad Anderson, Ph.D., for his instruction on forecasting and guidance on this project. I would also like to thank Mr. Lee Winter of the TACC data division for his help in obtaining a very specific data set in a short amount of time. The biggest thanks go to my wife for supporting me and encouraging me throughout the research process.

Maj Theodore A. Langstroth

Table of Contents

List of Figures

List of Equations

FORECASTING DEMAND FOR KC-135 SORTIES: DEPLOY TO DWELL IMPACTS

I. Introduction

General Issue

The primary mission of the US Air Force is to organize, train, and equip forces to be employed by a combatant commander in the accomplishment of his mission (AFDD 1, 2011:42). However, the USAF currently faces a challenge balancing this mission with long term sustainment of the crew force. This imbalance currently results in high deploy to dwell ratios for aircrews in all five major weapons systems of the mobility fleet. Headquarters Air Mobility Command (HQ AMC) A9 reports that active duty KC-135 aircrew members operate under a 1:1.3 deploy to dwell ratio. This means that on average, a KC-135 aircrew member will have 1.3 days at home station for every day deployed or assigned to temporary duty (TDY).

The deploy to dwell ratio is undoubtedly a quality of life issue, but it has additional relevant consequences. Those days at home station are not time off. With only 206 days at home station, a KC-135 aircrew member still needs to accomplish required ground training, proficiency flight training, and perform their assigned duties. According to HQ AMC A9/AA9, the short term goal for the KC-135 active duty aircrew deploy to dwell ratio is 1:2. Achieving this target would provide aircrew members an additional 37 days at home station to accomplish requirements. The long term goal is 1:3, which would provide an additional 67days compared to the current state.

The KC-135 aircrew deploy to dwell ratio issue is a symptom of two independent factors: the size of the crew force and mission requirements. As AMC believes the deploy to dwell ratio is too high, the crew force is not sized appropriately for the mission set. Achieving the desired deploy to dwell ratio requires an increase in the size of the crew force, a decrease in mission requirements, or some combination of the two. However, each of these options has fiscal or operational costs which must be considered.

Problem Statement

AMC's KC-135 aircrew deploy to dwell ratio is currently 1:1.3, an undesirably low amount of time spent at home in relation to time spent TDY. The AMC goal for the KC-135 aircrew deploy to dwell ratio is 1:3, with an interim goal of 1:2.

Research Question and Hypotheses

This research will address the following question: What immediate actions can AMC take to improve the KC-135 aircrew deploy to dwell ratio from the current level of 1:1.3 to the desired short term goal of 1:2?

In order to answer this question, the research poses two hypotheses related to AMC's concern over the high KC-135 aircrew deploy to dwell ratio. The first deals with the feasibility of removing a non-optimal refueling mission set. The second focuses on assessing demand for KC-135 sorties worldwide.

Hypothesis 1 posits that AMC can improve the deploy to dwell ratio of KC-135 aircrew members by reducing or eliminating a specific mission set: KC-135 sorties flown in support of fighter movements over the continental United States (CONUS). Support for this hypothesis requires evidence that CONUS fighter movements comprise a

significant portion of all KC-135 sorties. Support for this course of action will also

require analysis indicating that CONUS fighter air refueling is a non-optimal mission, the

costs of which outweigh benefits to combatant commanders.

Hypothesis 2 posits that demand for KC-135 sorties is decreasing over time,

which will result in a lower deploy to dwell ratio for KC-135 aircrew members. Proving

this hypothesis requires forecasting and analysis of trends in KC-135 sortie data. This

research will use quantitative and qualitative methods to determine future demand for

KC-135 sorties. Future sortie activity will provide one indicator of how AMC's KC-135

aircrew deploy to dwell ratio will behave.

Research Focus

The KC-135 aircrew deploy to dwell ratio is a function of the number of available

aircrews and the mission set required of those aircrews. This research focuses on the

mission set and the resultant demand for KC-135 sorties, rather than the supply of

available aircrews. The KC-135 deploy to dwell issue could be solved by simply

increasing the number of KC-135 aircrew members. However, based on the current

fiscal environment, analysis of the demand for KC-135 sorties is more likely to suggest a

feasible solution.

This research focuses on available data sets from Operation Iraqi Freedom (OIF),

Operation Enduring Freedom (OEF), and 618 Air Operations Center Tanker Airlift

Control Center (TACC). These data sets will provide the foundation for quantitative

forecasting analysis. The OIF data will be analyzed for trends as operations in Iraq came

to an end. These trends could be analogous to future trends in OEF data. The TACC

data analysis will ensure sorties are not simply transferred from one theater to another, resulting in no overall change in the demand for KC-135 sorties.

Investigative Questions

In order to address Hypothesis 1, this research poses two questions:

- How many KC-135 air refueling sorties does AMC provide in support of CONUS fighter movements?

- What is the cost of those sorties to AMC in relation to the benefit for the ultimate customer, the combatant commander?

The answers to these questions will identify whether air refueling fighter aircraft on CONUS movements is a sub-optimal practice which should be discontinued in light of the current KC-135 aircrew deploy to dwell issue.

Investigation of Hypothesis 2 raises another series of questions:

- What trends exist in the number of KC-135 sorties flown as OIF drew to a close?

- Can those trends be extrapolated to forecast demand for KC-135 sorties as operations in OEF draw to a close?

- Was worldwide demand for KC-135 sorties affected by the end of OIF?

- What trends exist in overall demand for KC-135 sorties?

The answers to these questions will address how KC-135 aircrew deploy to dwell should behave, assuming the crew force remains at current levels.

Methodology

This research will pursue two primary methodologies to address the hypotheses on AMC's KC-135 aircrew deploy to dwell issue. The first will quantify AMC's use of

KC-135 sorties in support of fighter movements where air refueling is a convenience, rather than a necessity. The second involves use of quantitative forecasting techniques to determine whether total demand for KC-135 sorties is decreasing over time. If a decreasing trend exists, this research will attempt to quantify that trend's impact on the KC-135 aircrew deploy to dwell ratio. The quantitative forecasting methods for this research include simple exponential smoothing, exponential smoothing with trend component, seasonality analysis, and moving average.

Assumptions/Limitations

The KC-135 aircrew deploy to dwell ratio is a complex problem comprised of multiple interrelated factors. In order to apply quantitative methods to the research question and hypotheses, this research makes several assumptions. These assumptions attempt to simplify the problem without negating the value of subsequent conclusions.

First, this research assumes that the data sets provided are accurate. In order for valid, meaningful conclusions from the data analysis, the data must reflect real world conditions. While there are possibly errors in the years of data provided, these errors are assumed to be random and of similar magnitude throughout the data. Errors distributed in this manner indicate data representative of actual conditions and valid sortie forecasts.

A second assumption is that exclusion of sortie information from United States Air Forces in Europe (USAFE) and Pacific Air Forces (PACAF) will not impact the analysis. The primary reason for this assumption is that the deploy to dwell ratio calculated by AMC does not include data from aircrew members assigned to USAFE or PACAF. As a result, KC-135 sortie demand in USAFE and PACAF will not impact the

deploy to dwell ratio. USAFE and PACAF aircrews provide some support to deployed operations. However, the relatively low magnitude of that support compared to support from AMC aircrews minimizes its impact on deploy to dwell ratio.

Additionally, this analysis of the KC-135 aircrew deploy to dwell issue assumes the supply of KC-135 aircrews remains constant. While the deploy to dwell ratio can be improved by significantly increasing the supply of aircrew, the current fiscal environment makes such a course of action unlikely. However, sustained high operations tempo could result in noticeable decreases in aircrew retention. Even if demand decreases, should the number of aircrews decrease correspondingly, the deploy to dwell ratio will remain unchanged. In order to quantify the impact of increasing or decreasing sortie demand on the KC-135 aircrew deploy to dwell ratio, this research assumes aircrew levels remain constant.

Finally, this research assumes all KC-135 sorties in each data set have similar average sortie durations. This assumption means sorties from the different data sets are equivalent with respect to their impact on the deploy to dwell ratio. Significantly longer average sortie durations can drive an increase in the number of aircrews required, due to flying hour limits and crew rest requirements established in Air Force regulations. Based on these regulations, flying 200 four hour sorties would require fewer aircrews than flying 200 twelve hour sorties with a sustained high operations tempo. However, assuming similar average sortie durations means this effect would be equal across data sets.

Implications

The KC-135 aircrew deploy to dwell ratio at first glance appears to be a mere quality of life indicator for a subset of AMC. However, if the deploy to dwell issue continues to worsen, it could indicate a threat to the USAF Rapid Global Mobility Core Function. The KC-135 comprises the bulk of the USAF tanker fleet with 413 aircraft. If these assets are undermanned, the USAF's ability to project military power across the globe could be in jeopardy.

While acknowledging the current KC-135 aircrew deploy to dwell ratio is at an undesirable level, understanding which way the metric is trending can inform AMC leadership decisions in a variety of areas. Directly related to Hypothesis 1, AMC leadership could set policy on air refueling mission prioritization, including mission which will no longer be supported. From an acquisition standpoint, this research could inform decisions on the rate at which AMC retires KC-135 aircraft while it acquires new KC-46 airframes. From a training perspective, this information could suggest how to prioritize aircrew training across airframes. Should KC-135 aircrews be retrained into the KC-46, or should the new tanker draw on less heavily tasked airframes for its initial crew force?

Additionally, the methodology used in this research could be applicable to other airframes. While KC-135 aircrews currently have the worst deploy to dwell ratio in the mobility fleet, this research applied to all mobility airframes could indicate if another airframe's crew force is in more critical need of attention.

II. Literature Review

Chapter Overview

        This chapter begins with a brief discussion of the deploy to dwell ratio, the potential negative impacts of sustained high operations tempo, and factors which impact deploy to dwell. The chapter concludes with a summary of existing research using time series forecasting models.

Deploy to Dwell Background

        Air Force Policy Document (AFPD) 10-4 documents the intent and purpose of the Air and Space Expeditionary Force (AEF) construct. The USAF implemented the AEF to present forces for combatant commander requirements while maintaining readiness (AFPD 10-4, 2009:5). The AEF initially assigned airmen to four month vulnerability periods (bands) with four subsequent non-deployed periods, creating a 1:4 deploy to dwell ratio (AFPD 10-4, 2009:5). In 2009, the AEF was updated to include four additional bands with a longer six month vulnerability period and a range of deploy to dwell ratios. This updated construct acknowledged that less than half of all USAF career fields have the manning to achieve the targeted 1:4 deploy to dwell ratio (Wicke, 2008). The AEF assigns airmen to bands with deploy to dwell ratios ranging from 1:4 to 1:1 for the most stressed career fields (AFPD 10-4, 2009:5). Unfortunately, the AEF construct does not provide any relief for these stressed career fields. Instead, it attempts to improve quality of life by introducing predictable tour lengths while synchronizing the AEF with combatant commander requirements (Wicke, 2008).

However, KC-135 crew members fill a unique role as "Enablers." As Enablers, KC-135 crewmembers are not assigned to a specific AEF. This construct makes sense during periods of low operations tempo. Air refueling is a critical force enabler and force multiplier for any air operation. Assigning KC-135 crewmembers to an AEF may not be the most effective or efficient way to consistently meet combatant commander requirements. Crewmembers may be more effectively utilized at home station or saved for a contingency requiring their employment. However, sustained periods of high operations tempo have a powerful negative effect. Without the predictability, structure, and rule sets that the AEF construct provides, individual crewmembers suffer a perceived unsystematic assignment to deployment schedules. Additionally, the potential arises for inequities across the KC-135 crew force. Currently, individual wings are responsible for selecting the crew members for deployment with the aircraft. Training level, physical fitness, and even home station duties can result in higher deploy to dwell ratios for some aircrew members.

HQ AMC/A9 recently identified that mobility aircrew members operate at deploy to dwell ratios significantly higher than those spelled out in AFPD 10-4. Active duty KC-135 aircrew members have the worst deploy to dwell ratio, at 1:1.3. HQ AMC/A9 identified a target active duty KC-135 aircrew deploy to dwell ratio of 1:2 in the short term, with a long term goal of 1:3. General Johns, then commander of AMC, emphasized the importance of predictability for airmen in his 2012 testimony before congress: "To provide Global Reach for the Nation, we [AMC] must continually balance modernization and readiness, force structure and our Airmen" (Johns, 2012).

At first glance, deploy to dwell ratio appears to be merely a quality of life issue. However, when taken to extreme levels, the deploy to dwell ratio can be an indicator of more serious issues. At the tactical level, high deploy to dwell ratios can have detrimental impacts on flying safety. In a 2010 article, Lieutenant Colonel Larkins of AMC flying safety highlighted the negative impact of sustained high stress levels, citing sustained time away from home as a contributing factor in aviation stress (Larkins, 2010:5). On a larger scale, numerous studies point to detrimental effects on veterans deployed in support of OIF and OEF. Eisen et al discovered that mental and physical health was negatively impacted by deployment to Iraq or Afghanistan. (Eisen, 2012:S66). Polusny et al similarly found that soldiers returning to Iraq or Afghanistan showed increased symptoms of post-traumatic stress disorder (PTSD) and depression compared to first time deployers (Polusny, 2009:353). This research does not suggest that the deployment experiences of KC-135 aircrew and soldiers in ground combat are the same. Eisen et al found that in general, Air Force members reported fewer symptoms than Army or Marine service members (Eisen, 2012:S66). However, the possibility that repeated deployments have a negative impact on aircrew members should not be discounted. Ultimately, the poor quality of life indicated by a high deploy to dwell ratio could have long term impact on aircrew retention. This reduction in crew force creates a feedback loop which exacerbates the existing deploy to dwell ratio problem.

The Air Reserve Component (ARC) plays a critical role in determining the deploy to dwell ratio of active duty aircrew members. The ARC includes a vast force of KC-135 aircrew members that are essential for meeting combatant commander requirements. When the active duty crew force is insufficient to accomplish the mission, the Air

Reserve Component provides much needed manpower. Even without mobilization, volunteerism from Guard and Reserve units absorbs many of the sorties that would otherwise fall to their active duty counterparts. However, the level of ARC volunteerism is a complex issue in itself. Repeated lengthy deployments draw concern from employers (Kitfield, 2001:39).

Theoretical Models

Achieving the desired deploy to dwell ratio requires adjusting one of two variables: the size of the crew force or the required mission set. Each variable has a different theoretical model appropriate for optimization. AMC's concern over the current KC-135 aircrew deploy to dwell ratio suggests that the USAF has insufficient KC-135 aircrew members, or that the crew force is too heavily tasked.

Sub-optimization

In addition to providing KC-135s for combatant commander requirements in the theater of operations, AMC supports the movement of other assets required by combatant commanders. Fighter and other types of aircraft require air refueling support to transit an ocean to reach the theater. However, AMC also refuels fighter aircraft en route to the coast. This may be an example of a process optimized for one internal customer at the expense of another. From a supply chain management perspective, the process should be optimized from the perspective of the final customer, the combatant commander. Air refueling is an inherently inefficient mission. While CONUS fighter air refueling occurs daily, those sorties are required for aircrew proficiency training. Tanker boom operators require fighter contacts to maintain proficiency. Fighter aircrews require air refueling to

11

maintain combat mission ready status. This research will quantify the number of KC-135

sorties dedicated to CONUS air refueling and weigh the benefits of these missions

against the cost. The intent is to take a systems-wide perspective to assess whether

CONUS fighter air refueling is a sub-optimal policy.

Time Series Forecasting

Time series forecasting has applications in a variety of fields, ranging from

tourism to utility prices. Wang used time series to model tourist arrivals in Hong Kong

(Wang, 2004:367). Nogales et al used time series models to forecast future electric prices

(Nogales, 2002:342). There is also significant literature on the subject of airline demand

forecasting. Air carrier yield management models rely heavily on accurate demand

forecasting to maximize revenue. Weatherford et al studied the impact of erroneous

demand forecasts on airline revenue (Weatherford, 2002:811). While these documents

do not directly apply to this research, the prevalence of literature on time series

forecasting indicates the versatility and value of these techniques.

Existing research on forecasting demand for military aircraft focuses on models

for airlift rather than air refueling sorties. A 2004 AFIT thesis by Captain Huscroft

focuses on airlift aircraft availability. This model serves to predict the number of aircraft

available for tasking, but assumes the tasking level to be an independent variable

(Huscroft, 2004:iv). A 2012 thesis by Major DeYoung uses time series forecasting to

model demand for airlift requirements in Iraq and Afghanistan (DeYoung, 2012:21).

Major DeYoung notes that simple exponential smoothing provides the best model for

forecasting demand in Iraq with the drawdown complete (DeYoung, 2012:48). The

applicability of this conclusion to KC-135 sortie demand will be investigated in the data analysis chapter.

The literature review reveals that time series demand forecasting is a ubiquitous topic in multiple industries. These forecasting techniques have even been applied to military air cargo demand. However, the literature review did not uncover research on application of these techniques to air refueling. Existing research on air refueling deals primarily with efficient assignment of tankers to air refueling requirements. No research was discovered on predicting those requirements. Each of these elements impacts the overall problem of the KC-135 aircrew deploy to dwell ratio. Inefficient use of assets has the potential to worsen the problem. However, understanding demand for KC-135 sorties allows senior leadership to take a proactive approach in addressing this issue. This research fills a significant gap with its use of forecasting techniques to predict demand for the air refueling subset of mobility operations.

Summary

This chapter discussed the purpose of the AEF and its impact on KC-135 aircrew members as Enablers. It explained why deploy to dwell ratio is more than a quality of life issue and outlined some of the risks of sustained high operations tempo. Finally, the chapter reviews applications of time series demand forecasting. Although research on demand for KC-135 sorties was not evident in the literature review, time series forecasting has been used for both commercial aviation and military airlift applications. This research will fill a gap in the body of knowledge regarding understanding the demand for KC-135 refueling sorties.

III. Methodology

Chapter Overview

This chapter discusses the general methodologies used to analyze data for information to support the research hypotheses. Next, it covers the relative merits of specific time series forecasting techniques and provide the equations used in this research for generating the forecasts. Finally, this chapter discusses a quantitative means for assessing the relative merit of each forecasting technique and the equation used in this research to generate that assessment.

General Methodology

There are several methods to address AMC's KC-135 aircrew deploy to dwell issue. This research will use quantitative and qualitative techniques to assess future levels of demand for KC-135 sorties. This demand will in turn impact the core issue of the KC-135 aircrew deploy to dwell ratio.

This research will quantify the amount of support KC-135 aircrews dedicate to CONUS refueling of fighter aircraft on missions where ground refueling stops are possible. The analysis will exclude missions flown for aircrew proficiency training. While CONUS fighter air refueling occurs daily, many of these sorties are necessary for aircrew proficiency training. Tanker boom operators require fighter contacts to maintain proficiency. Fighter aircrew members require air refueling to maintain combat mission ready status. Additionally, the analysis will exclude KC-135 sorties where refueling is essential to the fighter mission. Some test and airborne alert missions have a time sensitive nature that requires air refueling for mission accomplishment. Analysis of these

refueling sorties will assess whether CONUS air refueling support for fighter movements is a sub-optimal policy that benefits one portion of the USAF at a cost to AMC.

This research will also attempt to forecast future demand for KC-135 sorties based on historical data from three separate theaters of operations. Specifically, it will consider number of KC-135 sorties as the dependent variable and time as the independent variable. The analysis will make use of time series forecasting techniques including exponential smoothing, exponential smoothing with trend information, analysis of seasonality, and a moving average. These forecasts will be compared for merit based on mean absolute error and qualitative analysis of variability. Ultimately, these forecasts will be used to determine whether data supports Hypothesis 2.

The decision to use time as the independent variable rather than operational planning considerations is based on information availability. Operational planning provides combatant commanders with flexible options. However, this flexibility also creates uncertainty. While scripted events comprise part of operational planning, unforeseen events also play a major role. A regression model using operational considerations as independent variables could provide useful information on the need for KC-135 sorties. Unfortunately, this model would require inputs which will likely be unknown, especially in the long term. Unless specific operational inputs across all theaters for the time period of interest are known, the operationally based regression model will not output actionable results. A model based on operational considerations may be more valuable in the short run. However, after twelve years in Afghanistan, historical Air Tasking Order data provides a more utilizable indicator of KC-135 demand than the menu of options in the associated operations plan. For this reason, the research

will focus on a time series analysis of demand for KC-135 sorties that does not rely on operational inputs. However, this research acknowledges that many external operational factors will influence future operational activities.

Data sets for the demand analysis consist of sortie data from three separate groupings of operations. The first data set consists of monthly sortie data from OIF and covers the period from January 2003 to August 2010. The second data set consists of sortie data from OEF and covers September 2001 to December 2012. The final data set consists of sortie data from TACC tasked sorties across the globe from December 2004 to December 2012. TACC/XOND provided all three data sets.

Time Series Forecasting Models

Time series models are useful for making short-term forecasts when observed data hold to identifiable patterns over time (Fitzsimmons, 2011:458). Two relatively simple quantitative time series modeling techniques include the moving average and exponential smoothing. In order to incorporate trends in data, the exponential smoothing method can include a trend adjustment. Additionally, with a large enough data set, exponential smoothing forecasts can be further expanded to include the effects of seasonality.

Moving Average

A moving average is one of the simplest methods for forecasting while mitigating the impact of random events. The moving average takes N-1 time periods prior to the current observation and averages those observations with the current observation to obtain a forecast for the next time period. The strength of the moving average lies in its

simplicity. One weakness is that limited data points restrict the value of N to lower

numbers. However, with a robust data set, this is not an issue.

Equation 1 is the equation used to calculate a moving average forecast for KC-

135 sorties.

$$F_{t+1} = MA_t = \frac{A_t + A_{t-1} + A_{t-2} + \cdots + A_{t-N+1}}{N} \qquad (1)$$

Where:
F_{t+1} = forecast for period t + 1
MA_t = moving average for time period t
A_t = actual observation for time period t
N = number of time periods selected for the moving average

Another method for using the moving average to analyze data centers the average

around a given time period. While Equation 1 is useful for forecasting demand based on

historical data, the centered moving average is helpful when analyzing data for trends.

This comes into play during seasonality analysis, which will be discussed later.

Simple Exponential Smoothing

Exponential smoothing is a mathematical time series forecasting technique

frequently used to forecast demand. Based on the assumption that KC-135 sortie demand

varies with time, this technique is applicable to the problem of forecasting demand for

KC-135 sorties. Exponential smoothing takes the previous forecast and incorporates it in

the next time period's forecast. This technique has several advantages over the moving

average. Unlike the moving average, exponential smoothing does not discard older data

as time progresses (Fitzsimmons, 2011:459). However, these older data points receive

progressively less weight as more recent observations become available (Fitzsimmons,

17

2011:459). Finally, the calculation is relatively simple and only requires the most recent

data (Fitzsimmons, 2011:459).

Equation 2 is the equation used in the analysis for calculating smoothed demand

for KC-135 sorties.

$$S_{t+1} = \alpha(A_t) + (1 - \alpha)(S_t) \qquad (2)$$

Where:
S_{t+1} = smoothed forecast for period t + 1
α = smoothing constant
A_t = actual observation for time period t

The smoothing constant α is given a value between zero and one which provides

a relative weight for more recent data (Fitzsimmons, 2011:459). A value of zero for α

completely ignores actual data, ultimately resulting in a forecast value equal to the initial

forecast. A value of one for α ignores previous forecasts. This is also known as the

naïve forecast, where the forecast for period t + 1 is simply the observed value for period

t. In the naïve forecast, $F_{t+1} = A_t$. For exponential smoothing, the initial forecast is

assumed to be the initial actual value, or $S_1 = A_1$

Exponential Smoothing with Trend Adjustment

One weakness of the simple exponential smoothing forecasting method is that it

does not account for trends in data. Simple exponential smoothing forecasts will

continue to weight data based on the selected value of α without regard to increasing or

decreasing trends in data. As a result, forecasts will continuously fall short of or exceed

actual demand. Exponential smoothing with trend adjustment accounts for forecasting

error created by trends in data by adding an additional term.

Equations 3-5 are the equations used in the analysis for calculating smoothed

demand with trend adjustment for KC-135 sorties.

$$F_{t+1} = S_{t+1} + T_{t+1} \tag{3}$$

$$S_{t+1} = \alpha(A_t) + (1 - \alpha)(F_t) \tag{4}$$

$$T_{t+1} = \beta(S_{t+1} - F_{t-1}) + (1 - \beta)T_t \tag{5}$$

Where:
F_{t+1} = smoothed forecast including trend for period t + 1
S_{t+1} = smoothed forecast for period t + 1
T_{t+1} = trend component for period t + 1
α = smoothing constant
A_t = actual observation for time period t
β = trend component smoothing constant

Equation 3 simply states that the forecast demand for period t + 1 is comprised of

the exponential smoothing forecast for period t + 1 and the trend adjustment for period t

+ 1. Equation 4 is identical to Equation 2, with the exception of the last term including

trend adjustment. The constant β in Equation 5 is given a value between zero and one to

weight the importance of the trend component in the final forecast. A value of zero for β

ignores trend information. A value of one for β assumes all variation in the data can be

attributed to the trend. As with exponential smoothing without trend adjustment, the

initial value of the smoothed forecast is assumed to be the initial actual value,

$S_1 = A_1$. Additionally, the initial trend value is assumed to be zero, or $T_1 = 0$.

In order to objectively measure the accuracy of each forecast, the analysis must

quantify the difference between the observed number of sorties and the forecast number

of sorties. This error is calculated for each forecast method and for each value selected

for the constants α and β. One possible pitfall of simply averaging the error involves

high and low forecasts which could cancel each other out. A forecasting model could be

1000 high one month and 1000 low the next but still have an average error of zero. This

model would obviously not be preferable to a model which was consistently high by 100.

Taking the absolute value of the error before averaging negates this possibility. This

ensures positive and negative errors do not cancel each other out and falsely indicate an

accurate forecast.

Equation 6 is the equation for calculating the mean absolute deviation (MAD)

between forecast values and actual values.

$$MAD = \sum \frac{|A_t - F_t|}{n} \qquad (6)$$

Where:
MAD = mean absolute deviation
A_t = actual observation for time period t
F_t = forecast observation for time period t
n = number of forecasts

The MAD will indicate the quality of fit for various values of α and β and provide a

means for comparison between the forecasting methods.

In addition to quantitative analysis using MAD, assessing a forecast model

requires some qualitative analysis. The research accomplishes this qualitative assessment

by plotting observations and forecasts on the same graph. This provides a visual

depiction of the accuracy of the forecast and is useful for comparing forecasts with

similar values for MAD. A visual depiction can portray the sensitivity of the forecast

model with respect to one-time events, trends, and seasonality. The purpose of the forecasts generated in this analysis is to determine long term trends in data. In this light, forecasts that smooth peaks and valleys in the data are more desirable than a naïve forecast which simply chases the last period's demand. Combined with the quantitative value of MAD, this technique can provide more insight into the value of a forecast than a single number.

<center>Seasonality Analysis</center>

The final analytical method used to analyze the data seeks to quantify variations caused by seasonality. In the case of KC-135 sorties, hot summer months mean decreased aircraft performance and lower fuel loads available for offload to receivers. With the same mission requirements, more sorties will be required to meet demand. Trend analysis will misidentify these increases as an overall trend towards increased demand. Conversely, a decrease in demand coinciding with the summer could show a level demand. Trend analysis alone would fail to identify the decreased demand. Seasonality analysis entails taking a moving average of observations over the desired period, a year in this case. Based on whether the seasonal effect is multiplicative or additive, the average is divided into or subtracted from the observation to obtain an index for the given time period. To further eliminate variation, corresponding indices are averaged to obtain an overall index. In analysis over a year, this process results in an index for each individual month.

<center>21</center>

Summary

This chapter covered the general methodologies selected to analyze data sets for evidence in support of the research hypotheses. It discussed the relative merits of moving averages, exponential smoothing, trend analysis, and seasonality, along with the equations used to generate forecasts with those techniques. Finally, this chapter discussed the importance of using absolute deviation as a quantitative measure of each forecasting technique and provided the equation used in this research to generate that value.

IV. Analysis and Results

Chapter Overview

This chapter discusses the results of the forecasting techniques discussed in Chapter III. Initial Findings includes results of the simple exponential smoothing, exponential smoothing with trend analysis, and seasonality analysis. These analyses are grouped by forecasting method to demonstrate the relative merit of each technique. Final Data Analysis includes the same forecasts using annual data rather than monthly, as well as a forecast using an aggregate of all three data sets. The analyses in this section are grouped by data set to highlight overall conclusions. Finally, the Time Series Regression section discusses trends in data and the statistical confidence in basing conclusions on those trends.

Initial Findings

With respect to Hypothesis 1, analysis of AMC data for KC-135 sorties did not reveal a significant number of sorties dedicated to air refueling in support of fighter movements over the CONUS when ground stops were possible. HQ AMC/A3RI reported that TACC historical data does not include the level of detail required to differentiate air refueling support to fighter aircraft on CONUS movements from trans-oceanic support (AMC A3/A3RI, 2013). The data includes departure and arrival points of tanker aircraft, but not of the fighter receivers. As a result, sorties that appear to support CONUS fighter movements could be part of a larger effort where the fighter receivers continue across the ocean. Additionally, CONUS departure and arrival points could be the result of tanker or receiver mission aborts due to weather or maintenance

23

issues. Despite this lack of quantitative support, HQ AMC/A3RI provides a qualitative analysis. The consensus of HQ AMC/A3RI is that "AMC does not provide CORONET like support for CONUS to CONUS fighter movements" (AMC A3/A3RI, 2013). The Chief of Long Range Scheduling of the 6th Operations Support Squadron at MacDill Air Force Base confirms this assessment. Requests for tanker support for CONUS fighter movements from individual units are rampant (6 OSS/OSOS, 2013). However, TACC directed missions in this category are scarce, if not non-existent (6 OSS/OSOS, 2013). Recent TACC tasked missions that appear to support CONUS fighter movements were training related: pre-deployment preparation and large scale exercises directed by the Joint Staff (6 OSS/OSOS, 2013). Anecdotal evidence that AMC supports CONUS fighter movements was flawed. The missions in question were either in support of critical pre-deployment training or not directed by TACC. The HQ AMC/A3RI assessment with 6 OSS/OSOS confirmation is the only reliable information available. Data does not provide evidence to support Hypothesis 1, that AMC can improve the deploy to dwell ratio of KC-135 aircrew members by reducing or eliminating KC-135 sorties flown in support of CONUS fighter movements.

Simple Exponential Smoothing

The first forecasting technique applied to the data sets is simple exponential smoothing. The three data sets were analyzed using Equation 2 with values for α ranging from zero to one in increments of 0.1. To assess the relative merit of each value of α, the results were analyzed quantitatively with Equation 6 and qualitatively by plotting the results graphically.

Within the OIF data set, varying α from zero to one resulted in eleven forecasts. With the exception of $\alpha = 0$, all values of α resulted in similar values for MAD. Setting $\alpha = 0$ resulted in a MAD of 122 sorties. All other values of α resulted in a MAD ranging from 37 to 39. Five separate values for α (0.2, 0.3, 0.8, 0.9, and 1.0) resulted in the minimum MAD of 37. Figures 1-3 show plots of actual and forecast sorties for selected α values over the time period encompassed by the OIF data set.
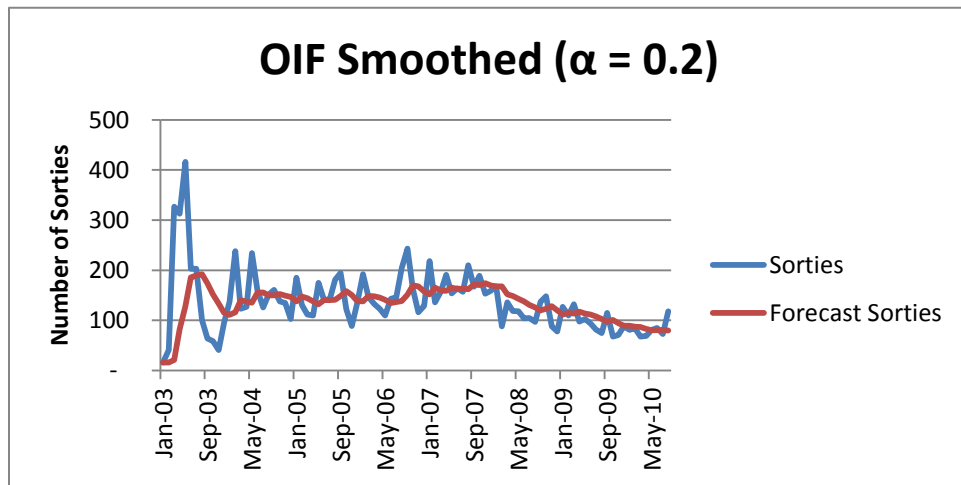
Figure 1: OIF Data Smoothed ($\alpha = 0.2$)
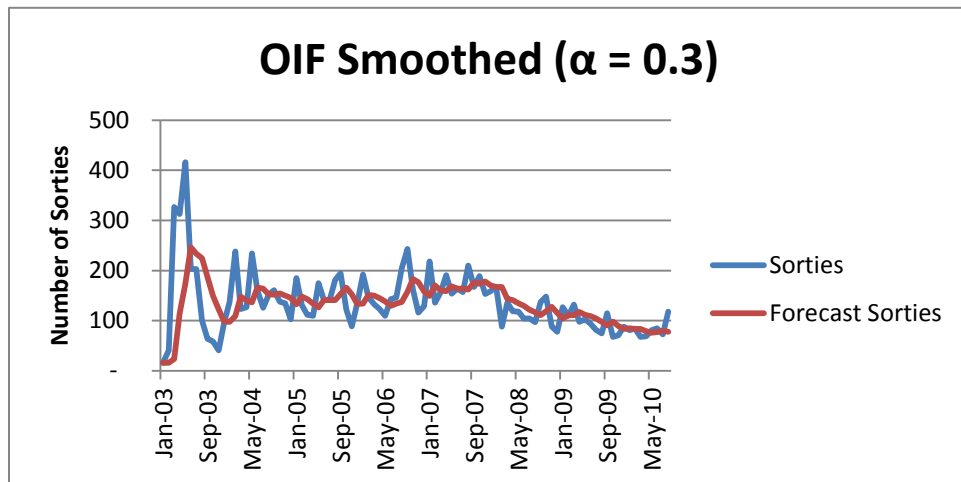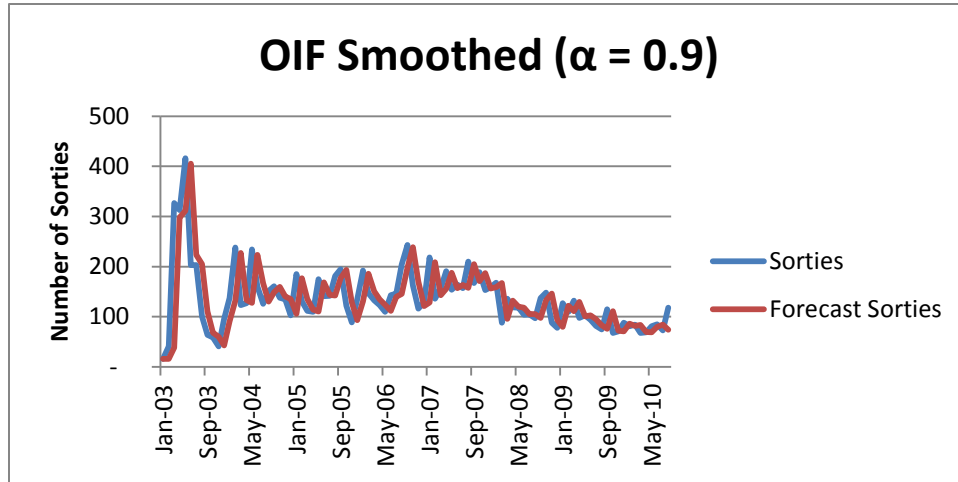

Figure 2: OIF Data Smoothed ($\alpha = 0.3$)

Figure 3: OIF Data Smoothed (α = 0.9)

Although five of the forecasts have the same MAD, qualitative analysis of the plots provides insight into which value of α results in the best forecast. Values of α approaching 1.0 result in forecasts that simply chase the demand of the last period. Based on the data, low MAD for α values of 0.8, 0.9, and 1.0 are likely the result of steady state demand for the second half of the data set. Based on this qualitative analysis, α values of 0.2 and 0.3 yield the best forecasts by smoothing peaks and dips in demand.

Varying α from zero to one with the OEF data set resulted in another eleven forecasts. MAD ranged from 40 to 97, with the highest deviation again attributable to an α value of zero. However, all the low MAD values resulted from α values approaching one. Four values of α (0.7, 0.8, 0.9, and 1.0) resulted in the minimum MAD of 40. Figures 4-6 show plots of actual and forecast sorties for selected α values over the time period encompassed by the OEF data set.
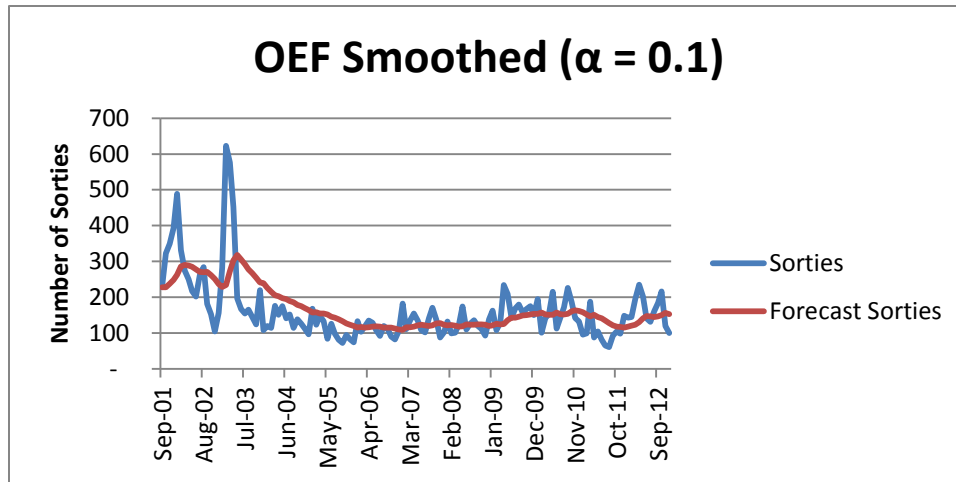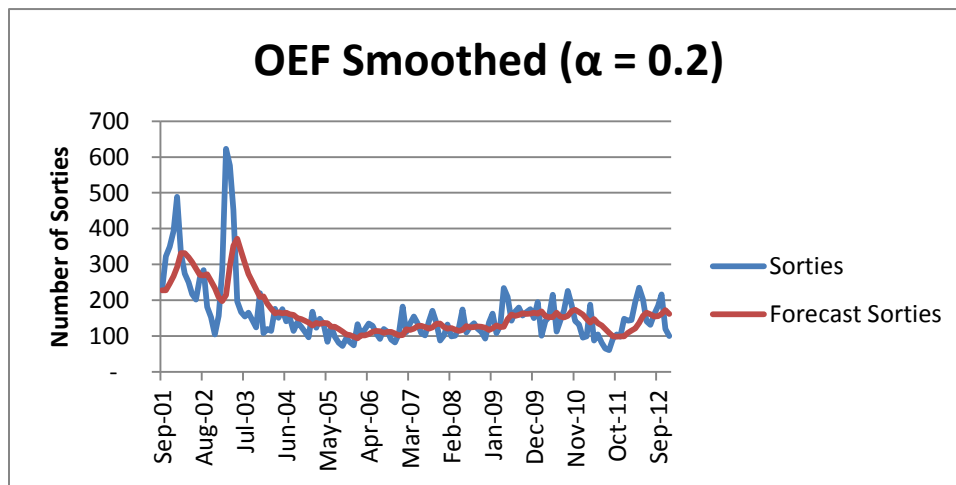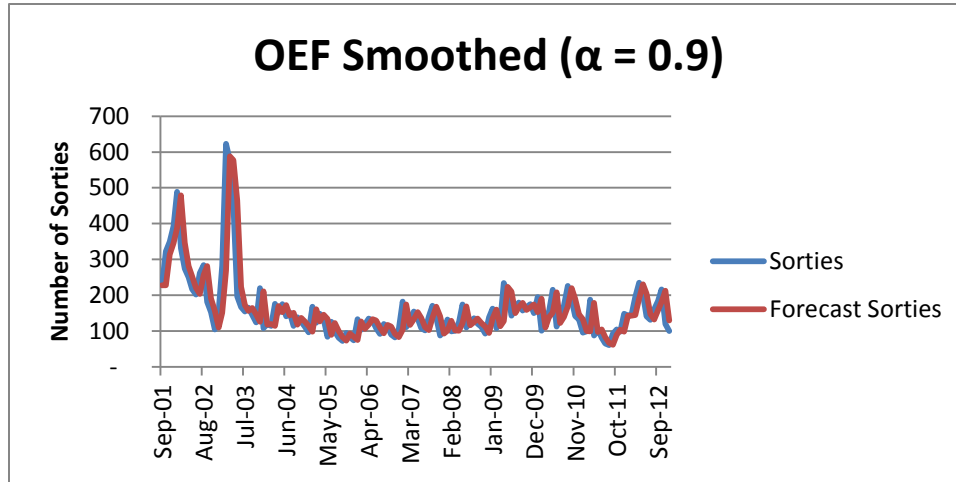
26

Figure 4: OEF Data Smoothed ($\alpha = 0.1$)

Figure 5: OEF Data Smoothed ($\alpha = 0.2$)

Figure 6: OEF Data Smoothed ($\alpha = 0.9$)

As with the OIF data set, lower MAD at higher α values is likely the result of relatively stable demand from June of 2004 to November 2010. Qualitative analysis demonstrates that an α value of 0.1 or 0.2 yields the best forecast without overreacting to blips in the data. Three months after the peak observation of 623 sorties in February 2003, the $\alpha = 0.1$ forecast overestimated demand by 121 sorties. The $\alpha = 0.7$ forecast overestimated by 286. This example demonstrates the danger of overreliance on pure quantitative measures like MAD. An α of 0.1 resulted in a MAD of 50, while an α of 0.2 resulted in a MAD of 46.

Varying α from zero to one with the TACC data set again resulted in eleven forecasts. MAD ranged from 93 to 150, with an α value of zero again generating the highest MAD. As with the OEF data set, all the low MAD values resulted from α values at the upper end of the range. Three values of α (0.7, 0.8, and 0.9) resulted in the minimum MAD of 93. Figures 7-9 show plots of actual and forecast sorties for selected α values over the time period encompassed by the TACC data set.
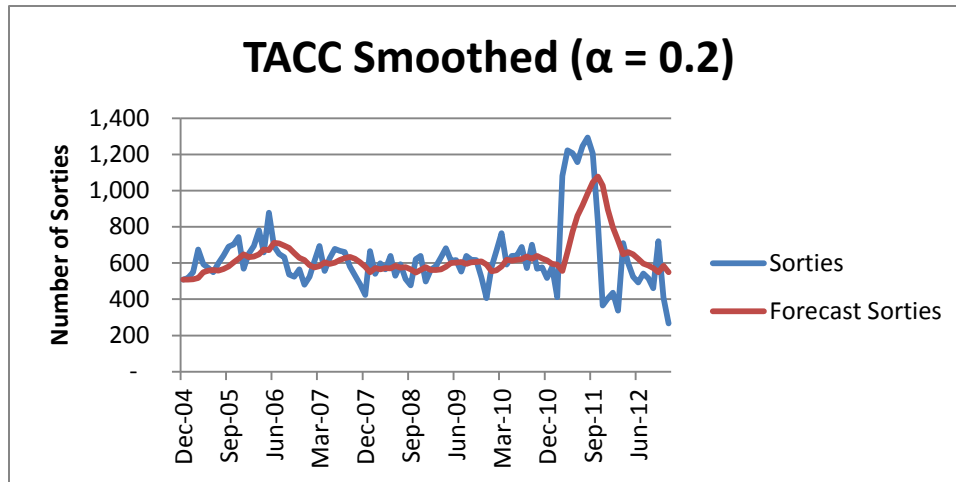
28
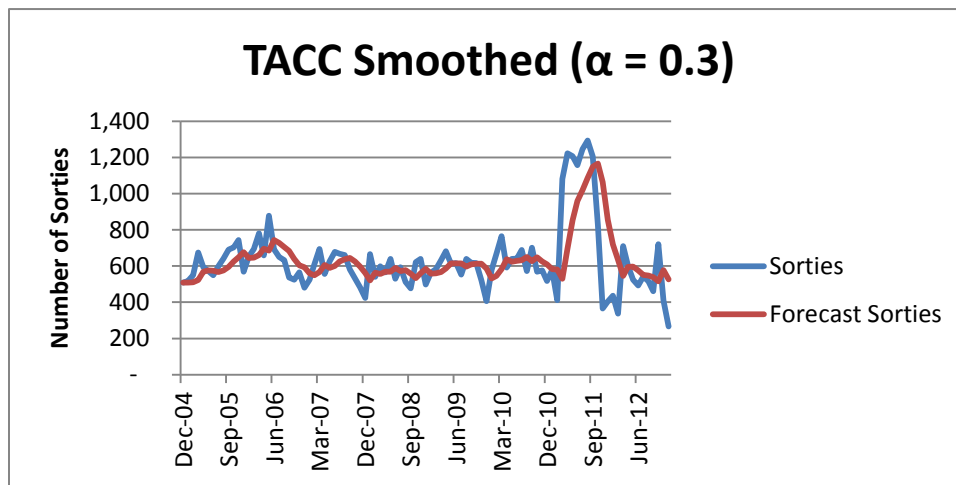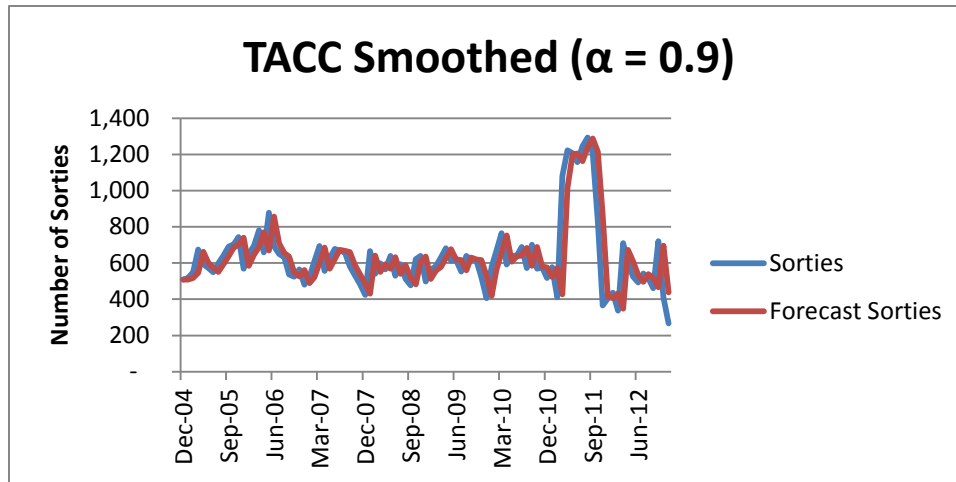
Figure 7: TACC Data Smoothed ($\alpha = 0.2$)

Figure 8: TACC Data Smoothed ($\alpha = 0.3$)

Figure 9: TACC Data Smoothed ($\alpha = 0.9$)

As with the previous two data sets, the low MAD at high values of α is likely the result of the relatively stable demand for KC-135 sorties with the exception of March through October 2011. Once again, qualitative analysis of the plots favors the forecasts using an α of 0.2 or 0.3, despite their higher MAD. An α of 0.2 resulted in a MAD of 115, and an α of 0.3 resulted in a MAD of 107. A difference of 24 in MAD between α of 0.9 and α of 0.3 is less bothersome when the magnitude of TACC KC-135 sorties is considered. With the exception of the obvious spike, the data averages about 600 sorties a month.

MAD provides a starting point for assessing the validity of a forecast. The exponential smoothing forecasts with the lowest MADs were invariably at α values approaching one. This analysis suggests that forecasting demand for KC-135 sorties may be less helpful than merely observing trends in the raw data. However, when viewing actual and forecast sortie data graphically, α values around 0.2 did not overreact to spikes in the data. This shows the value of a qualitative analysis in conjunction with

quantitative methods. Overall, the plots of forecast and actual sorties show a steady decrease in sorties for OIF data, and a relatively stable demand for sorties in the OEF and TACC data sets.

Exponential Smoothing with Trend Component

The next forecasting technique applied to the data sets is exponential smoothing with trend adjustment. The three data sets were analyzed using Equations 5-7 with values for α and β ranging from zero to one in increments of 0.1. To assess the relative merit of each combination of α and β, the results were analyzed quantitatively for MAD with Equation 10 and qualitatively by plotting the results graphically.

Within the OIF data set, varying α and β from zero to one resulted in 121 forecasts with   values for MAD ranging from 37 to 828. Fourteen combinations of α and β resulted in the minimum MAD of 37. Five of the forecasts with minimum MAD are identical to the simple exponential smoothing forecasts since the value for β was zero (α of 0.2, 0.3, 0.8, 0.9, and 1.0) The remaining low MAD forecasts included heavy emphasis on the trend component with β values ranging from 0.7 to 1.0. Figures 10-12 show plots of actual and forecast sorties for selected α and β values over the time period encompassed by the OIF data set.
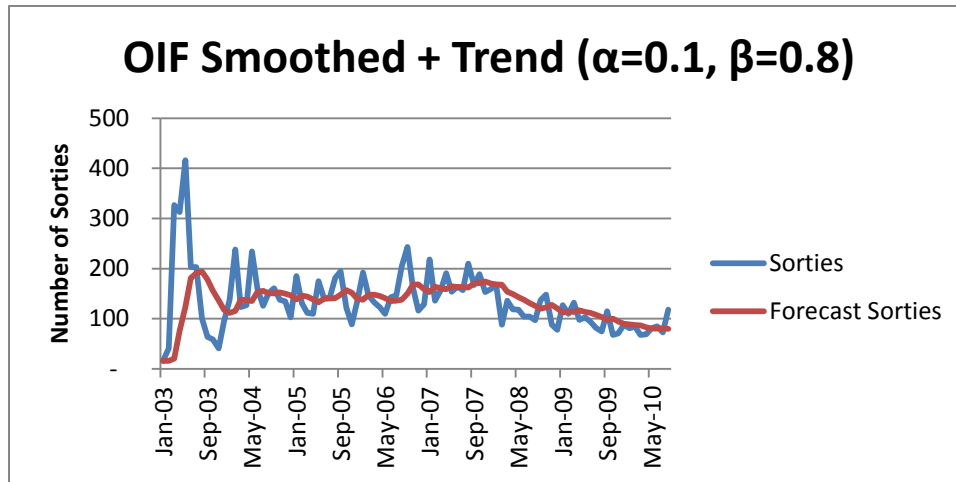
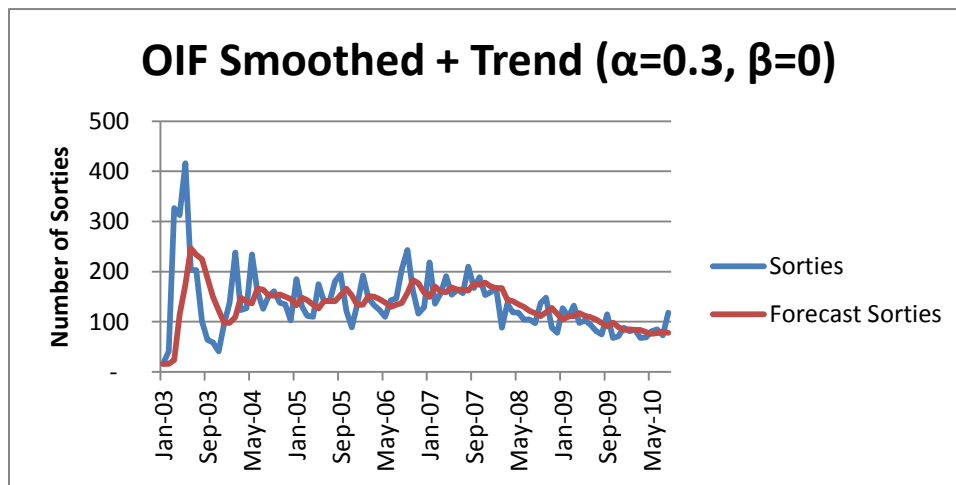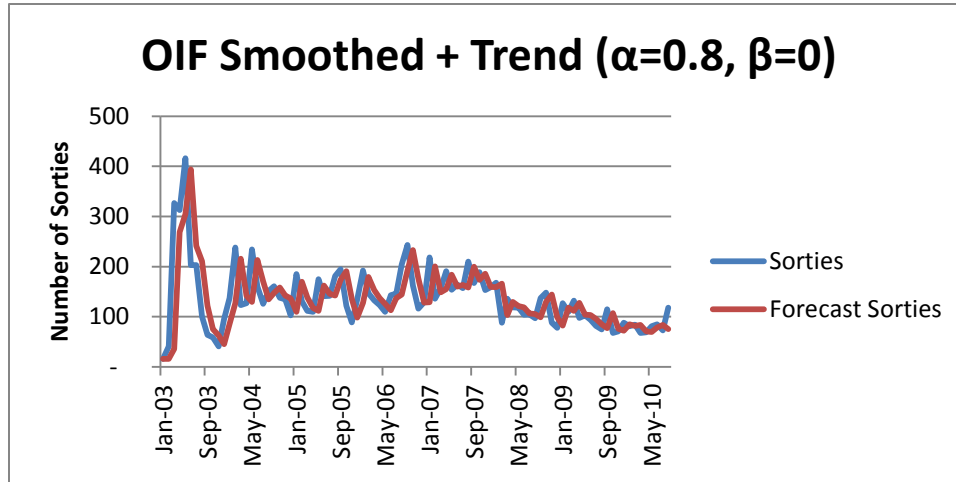**Figure 10: OIF Data Smoothed with Trend ($\alpha = 0.1$, $\beta = 0.8$)**

Figure 11: OIF Data Smoothed with Trend ($\alpha = 0.3$, $\beta = 0$)

Figure 12: OIF Data Smoothed with Trend ($\alpha = 0.8$, $\beta = 0$)

Eight of the minimum MAD forecasts occurred at relatively high values of α, resulting in forecasts that chase the last month's observation and closely resemble Figure 12. The forecast depicted in Figure 11 is identical to that depicted in Figure 2, since the value for α is the same, and β is zero. An additional piece of information provided by the forecast including trend when β was high is the consistent negative trend in OIF KC-135 sorties from approximately 2008.

Varying α and β from zero to one with the OEF data set again resulted in 121 forecasts with values for MAD ranging from 40 to 97. Four combinations of α and β resulted in the minimum MAD of 40. These forecasts are all identical to the simple exponential smoothing forecasts since the value for β was zero (α of 0.7, 0.8, 0.9, and 1.0). Reviewing α values that provided low MAD with simple exponential smoothing indicated that high values for β increased MAD consistently for all values of α. Figures 13-15 show plots of actual and forecast sorties for selected α and β values over the time period encompassed by the OEF data set.
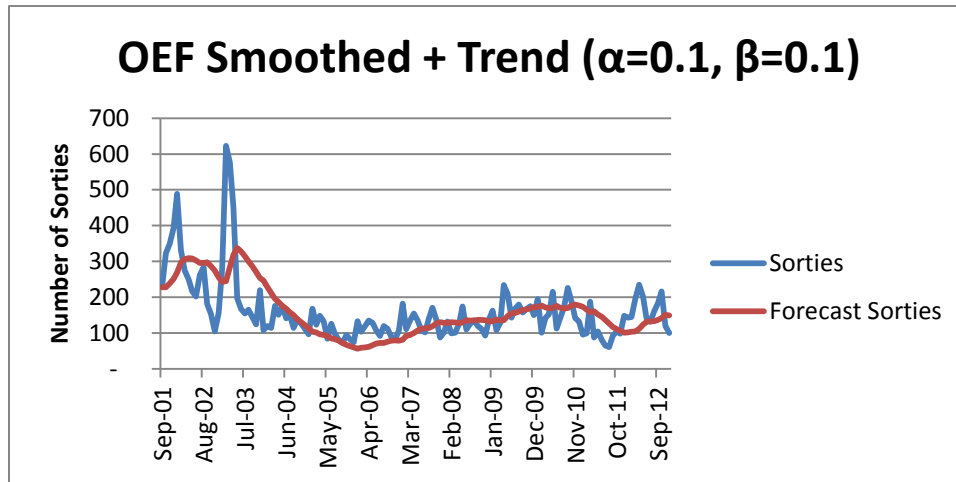
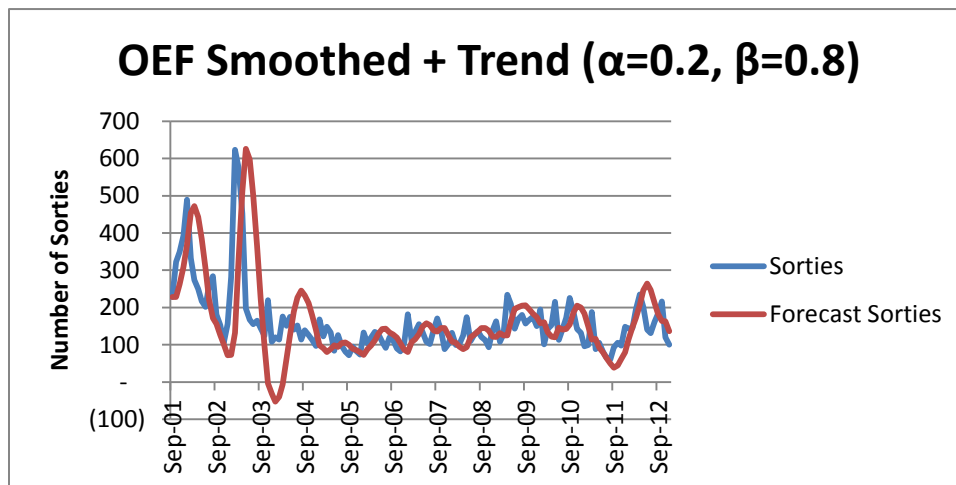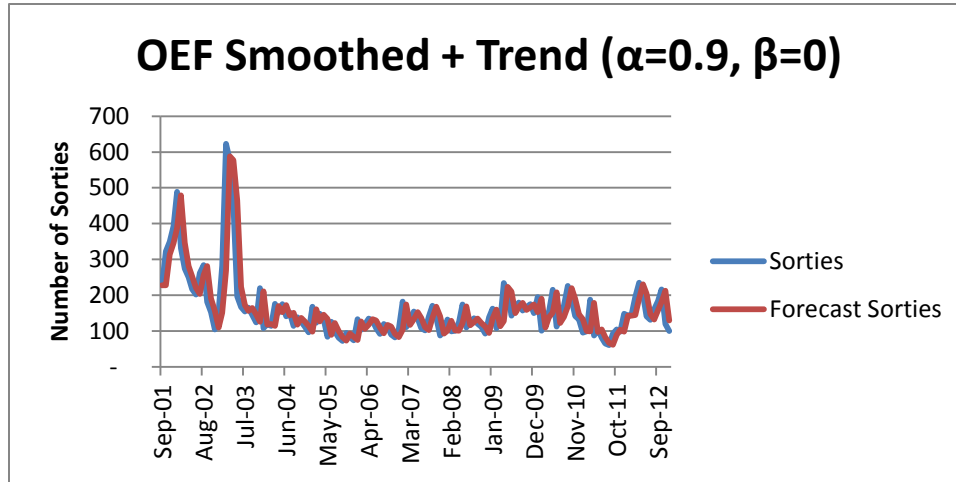**Figure 13: OEF Data Smoothed with Trend ($\alpha = 0.1$, $\beta = 0.1$)**

Figure 14: OEF Data Smoothed with Trend ($\alpha = 0.2$, $\beta = 0.8$)

Figure 15: OEF Data Smoothed with Trend ($\alpha = 0.9$, $\beta = 0$)

The plots of forecast sorties demonstrate why including the trend component does not result in a more accurate forecast for the OEF data set. For high values of β, the enormous spike in February 2003 and subsequent return to steady state operations introduce a great deal of error into the forecast. As a result, the forecast depicted in Figure 15 predicts a negative number of sorties from November 2003 to March 2004. With few exceptions, the trend component of the KC-135 sortie forecast appears to be about zero, which is consistent with steady state operations.

Applying exponential smoothing with trend adjustment to the TACC data set resulted in an additional 121 forecasts with MAD ranging from 93 to 1,977. Five combinations of α and β resulted in the minimum MAD of 93. All but two of these forecasts are identical to the simple exponential smoothing forecasts since the value for β was zero (α of 0.7, 0.8, and 0.9). The remaining low MAD values came at a single α value of 0.4, with β values of 0.9 and 1.0. Unlike the OEF data set, β did not have a consistent effect on MAD. In general, forecasts with α values less than 0.6 showed a

decrease in MAD as β increased. Values of α equal to or greater than 0.6 showed an increase in MAD as β increased. Figures 16-18 show plots of actual and forecast sorties for selected α and β values over the time period encompassed by the OEF data set.
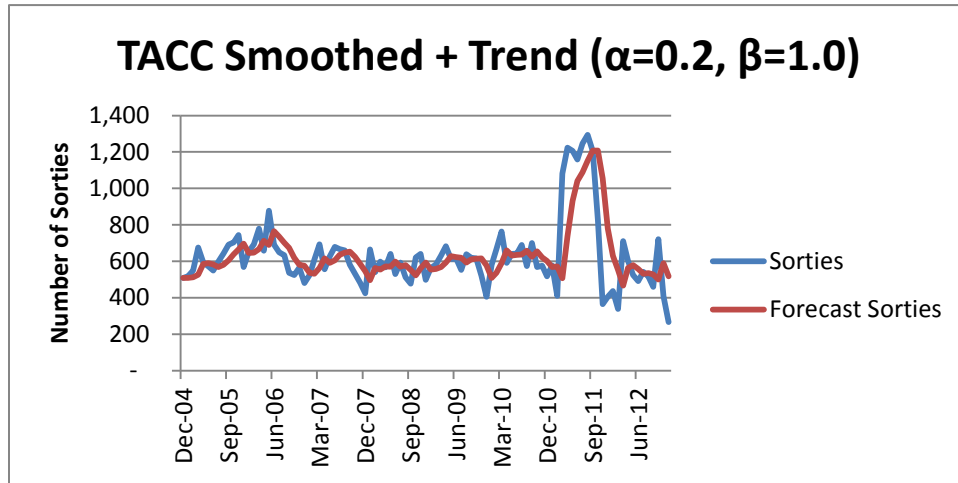

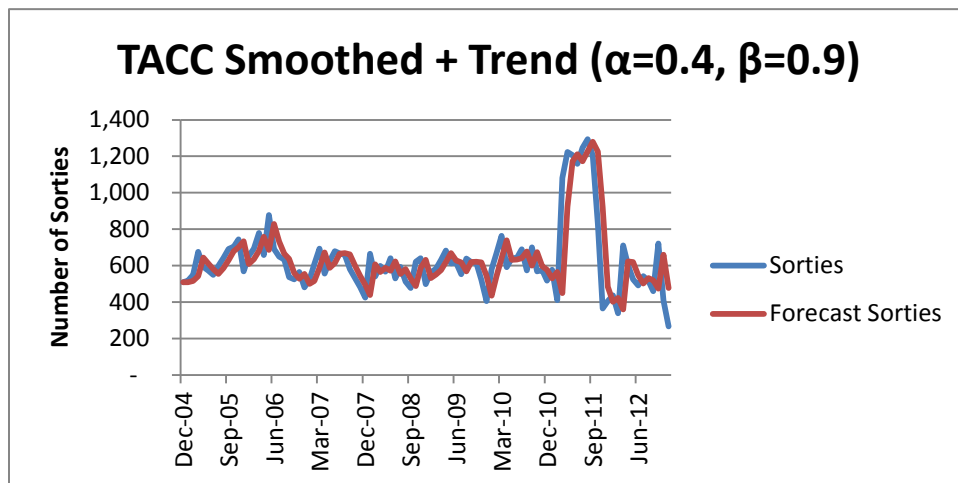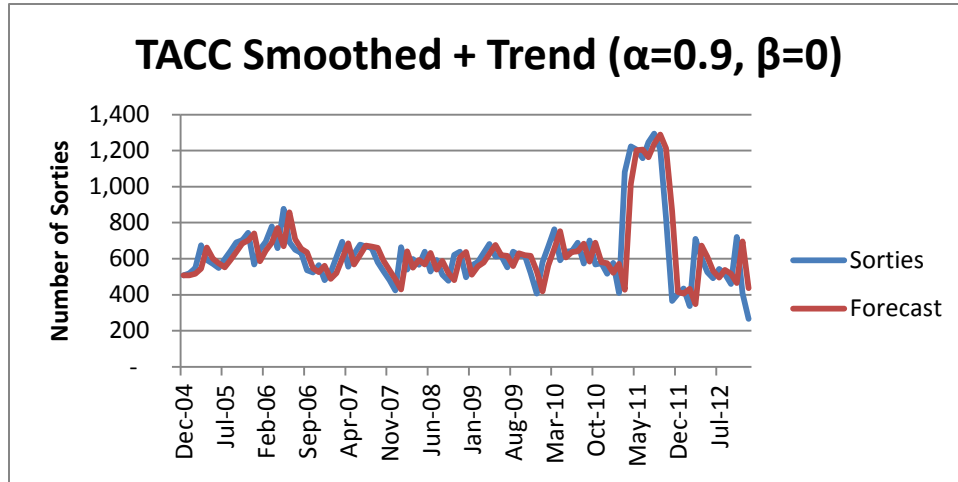**Figure 16: TACC Data Smoothed with Trend (α = 0.2, β = 1.0)**

Figure 17: TACC Data Smoothed with Trend (α = 0.4, β = 0.9)

36

Figure 18: TACC Data Smoothed with Trend (α = 0.9, β = 0)

The plots of TACC data forecasts do not explain why adding a trend component to the simple exponential smoothing model did not improve the forecast. The TACC data includes a large spike from March to September 2011, similar to the OEF data set. However, the relationship between β and MAD in the TACC data is not as clear as in the OEF data. The large surge does not explain the interrelated effects of α and β on forecasts in this data. The two data sets are similar in one regard, however. The TACC trend component also shows a relatively even distribution centered around zero, suggesting steady state operations.

For the data sets analyzed in this research, including a trend component in the exponential smoothing forecast did not improve the accuracy of the forecast from a quantitative perspective. Qualitatively, plots of forecast and actual sorties did not appear to be significantly more accurate with the inclusion of the trend component. However, viewing the trend component separately for feasible forecasts with high values for β provided some qualitative information regarding demand for KC-135 sorties in all three

37

data sets. As expected, data for OIF showed a negative trend until reaching a steady state demand of approximately 100 KC-135 sorties a month. With few exceptions, OEF and TACC data both show relatively stable demand with the trend component deviating around the zero point. This information will be helpful in drawing final conclusions.

Seasonality Analysis

The final component of an exponential smoothing forecast is seasonality analysis. This technique attempts to identify seasonal trends within the data which may cause simple exponential smoothing or trend analysis to chase observed demand. Unfortunately, the three data sets analyzed did not show significant seasonality, resulting in no improvement to the initial simple exponential smoothing forecast. However, the results of the seasonality analysis will be presented.

OIF data displayed some seasonality, with peak seasonality indices in May and September of 1.24 and 1.13 respectively. The lowest index occurred in November at a value of 0.74. With the exception of those extremes, however, seasonality indices remained very close to one for most of the year. Figure 19 shows a plot of seasonality index by month for the OIF data set with a seasonality index of one highlighted in red.
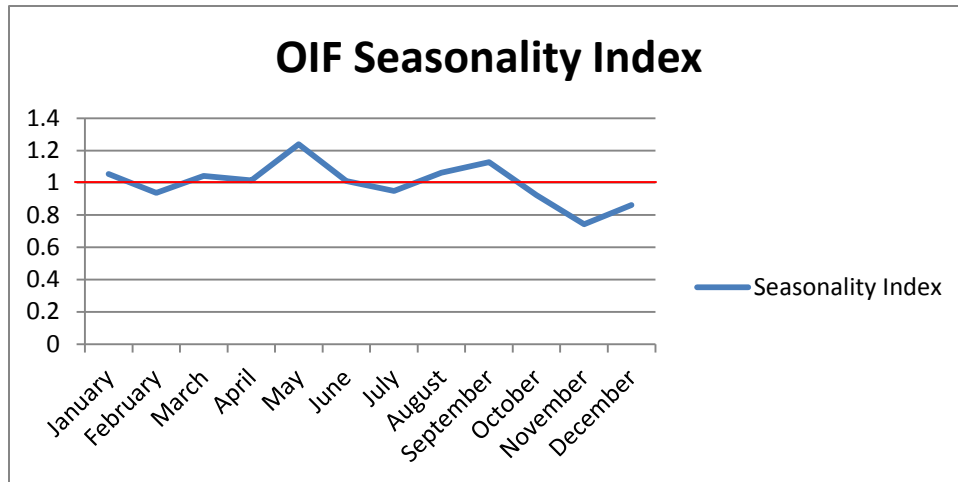
Figure 19: OIF Seasonality Index by Month

OEF data did not display a high level of seasonality. Within the OEF data set, the

highest seasonality index of 1.2 occurred in March, while the low of 0.84 occurred in

November. However, the indices for most months remained close to a value of one. The

peak indices are likely the result of operational considerations rather than environmental

factors. Figure 20 shows a plot of seasonality index by month for OEF data with a

seasonality index of one highlighted in red.
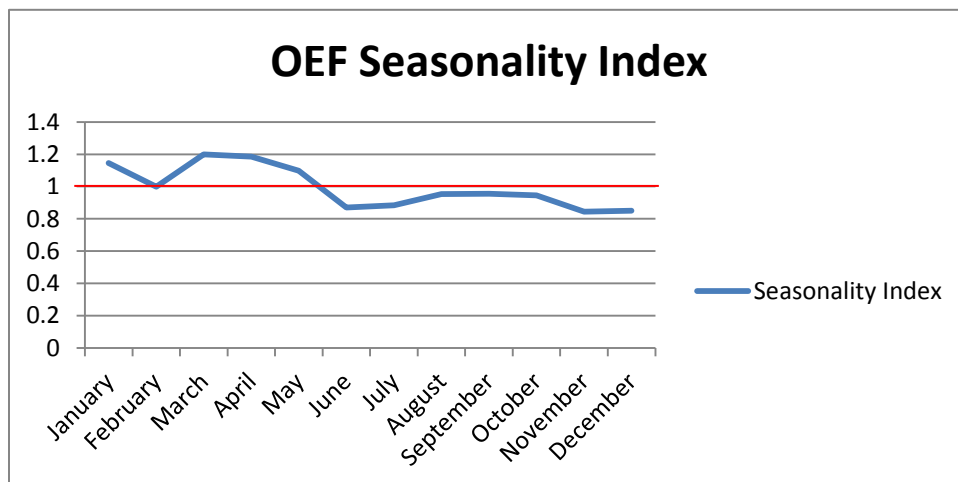
Figure 20: OEF Seasonality Index by Month

The seasonality indices for TACC data appear even more stable than the previous data sets. For most of the year, the seasonality index remains within 0.1 of one. The exceptions include a high in March of 1.17and a low of 0.73 occurring in December. The low values in November and December are likely the result of fewer aircraft flying during the holidays. Figure 21 shows a plot of seasonality index by month for TACC data with a seasonality index of one highlighted.
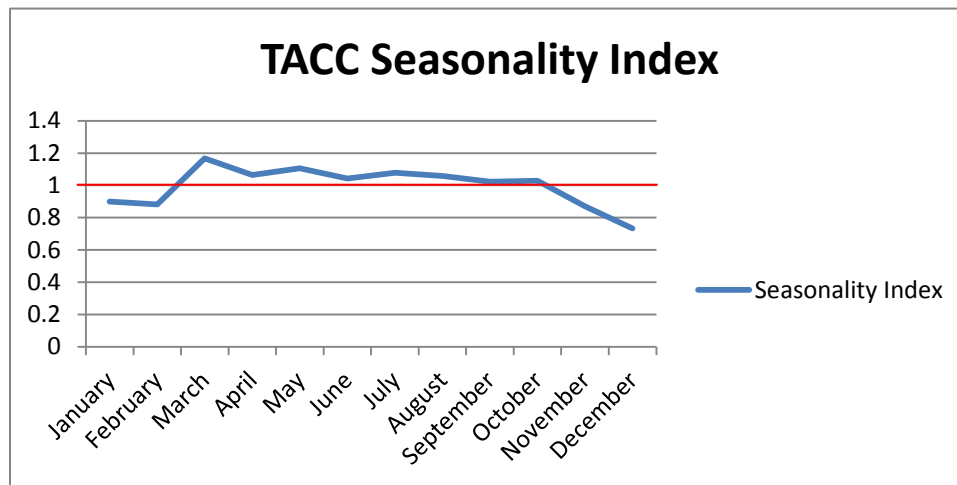
Figure 21: TACC Seasonality Index by Month

Ultimately, the seasonality analysis did not provide information useful for supporting or disproving Hypothesis 2. Seasonality does play a role in the monthly variation in sorties. All three data sets generally had the highest seasonality index in the spring, with minimum indices occurring in the winter. However, seasonality analysis did not add to the information revealed by exponential smoothing with trend adjustment. The possibility for increased or decreased demand for KC-135 sorties in certain months is useful for operational planners, but not as relevant for long term considerations.

Initial Findings Summary

The initial data analysis offered several lessons. In some cases, the simplest methods can provide the most valuable forecast. Within each data set, the simple exponential smoothing technique yielded the best MAD. Adding the trend component never resulted in a more accurate forecast. Qualitative analysis of forecast plots also did not reveal the forecasts including a trend component to be significantly more accurate than the simple exponential smoothing forecasts. Additionally, the analysis showed the importance of focusing on a long term perspective. The seasonality analysis provided no insight to the problem of forecasting long term demand for KC-135 sorties. The information focused on short term monthly variations, rather than the long term information needed to understand the future of the KC-135 aircrew deploy to dwell ratio.

The intent of analyzing each data set independently was to identify trends in individual theaters. That information could be used to predict future trends in other theaters. Specifically, trends from the closing months of operations in Iraq could be used as an analogy to predict demand for KC-135 sorties in Afghanistan as military operations draw down in that theater. However, the exponential smoothing techniques only forecast one period into the future. Using monthly data only provides a single month's forecast. Since the most recent data came from December 2012, the benefit of that forecast has already passed. The irrelevance of seasonality analysis also highlights the importance of focusing on longer time periods to draw meaningful conclusions with respect to impact on the KC-135 aircrew deploy to dwell ratio.

However, the forecast and sortie analysis did indicate an important fact. The final OIF data point in August 2010 indicated demand for approximately 80 KC-135 sorties.

When demand for those 80 sorties disappeared the next month, OEF and TACC data did not indicate a corresponding increase. TACC data showed an enormous increase in KC-135 sorties from March to September 2011, of approximately 600 sorties. After this spike, however, demand returned to previous levels. In fact, the demand before the spike averaged 601 sorties per month, and the demand after the spike averaged 508 sorties per month. OEF data showed similar activity, with demand relatively unchanged after the conclusion of OIF. This suggests that AMC was not operating all available KC-135s, with demand for OIF sorties taking priority over TACC sorties. Instead, the end of OIF resulted in a decrease of KC-135 sorties flown worldwide. Similarly, the end of operations in Afghanistan should result in a lower demand for KC-135 sorties and positively impact the KC-135 aircrew deploy to dwell ratio.

In order to draw more meaningful conclusions on KC-135 sortie demand, this research will shift its focus in two areas. First, the data will be analyzed using a year as the time period rather than individual months. Second, the data will be aggregated into a single data set for analysis. The intent of this approach is to identify long term trends in the data. Additionally, this approach should provide insight into the big picture of KC-135 sortie demand in all theaters. This analysis will then combine information previously gathered on individual theater trends to provide a forecast for overall KC-135 sortie demand.

Final Data Analysis

The simple exponential smoothing and exponential smoothing with trend analysis were used again on all three data sets, but with an annual time period. The seasonality

method was excluded due to the use of annual time periods and no justifiable method for dividing years into seasons. Additionally, each data set was analyzed with the moving average technique.

OIF Data Set

In the OIF data set, the exponential smoothing forecast with an α of 1.0 resulted in the minimum MAD of 271. Adding the trend component resulted in a forecast with a MAD of 231 when α was 0.9 and β was 0.5. The quantitative improvement of the forecast with the addition of trend information suggests a strong trend component in the OIF data set. A three year moving average forecast resulted in a MAD of 247. Plots of the data show a clear downward trend for OIF data annually, as expected. Figures 22-24 show plots of the minimum MAD forecasts.
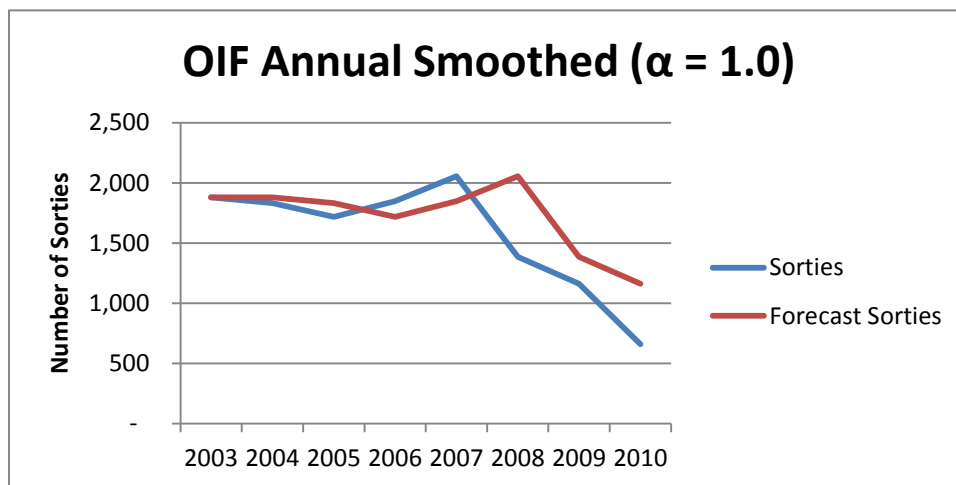
Figure 22: OIF Annual Data Smoothed ($\alpha = 1.0$)
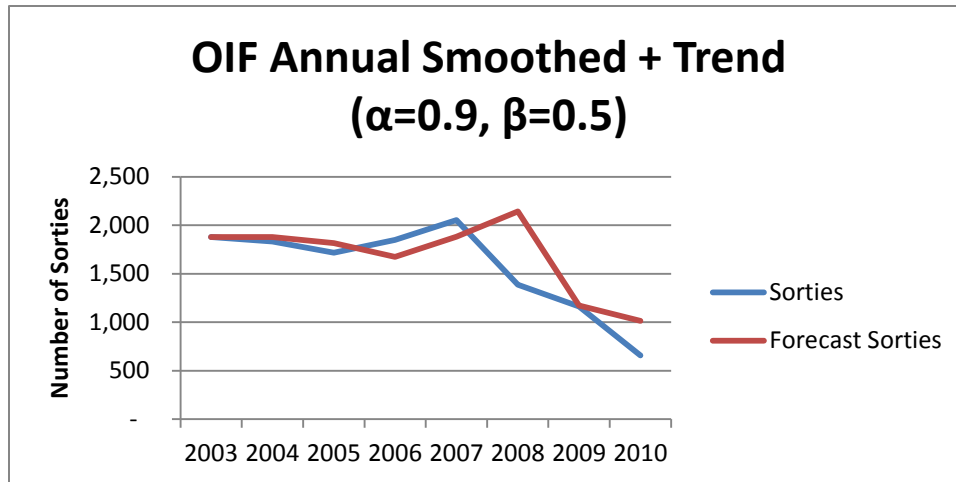
Figure 23: OIF Annual Data Smoothed with Trend (α = 0.9, β = 0.5)
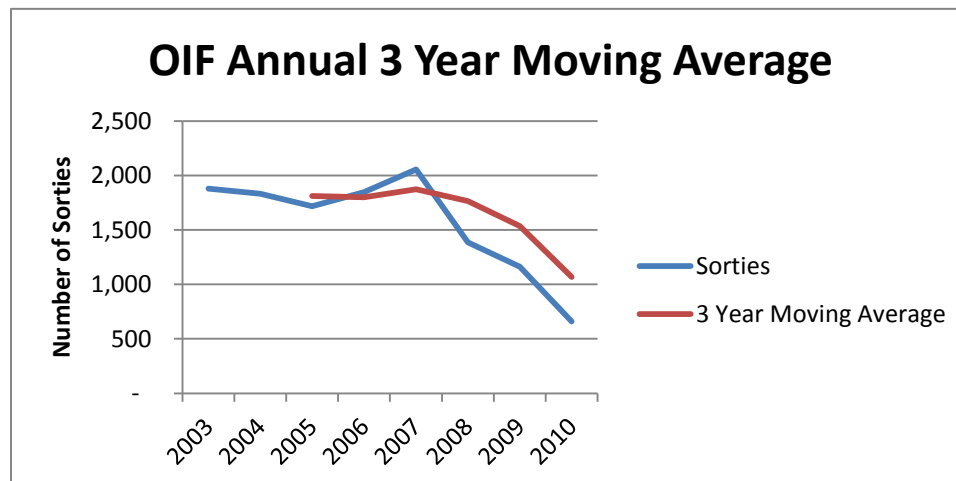
Figure 24: OIF Annual Data 3 Year Moving Average

OEF Data Set

In the OEF data set, the exponential smoothing forecast with an α of 0.1 resulted in the minimum MAD of 511. Adding the trend component resulted in a forecast with a MAD of 511 when α was 0.1 and β was 0, the same forecast. The lack of any change between the quantitatively best forecasts suggests no trend component in the OEF data set. Additionally, the relatively low values for α and β suggest a moving average may be

a more appropriate forecasting technique. A three year moving average forecast of annual OEF data resulted in a MAD of 392, a significant improvement on the exponential smoothing model. Figures 25 and 26 show plots of the minimum MAD forecasts for the OEF data.

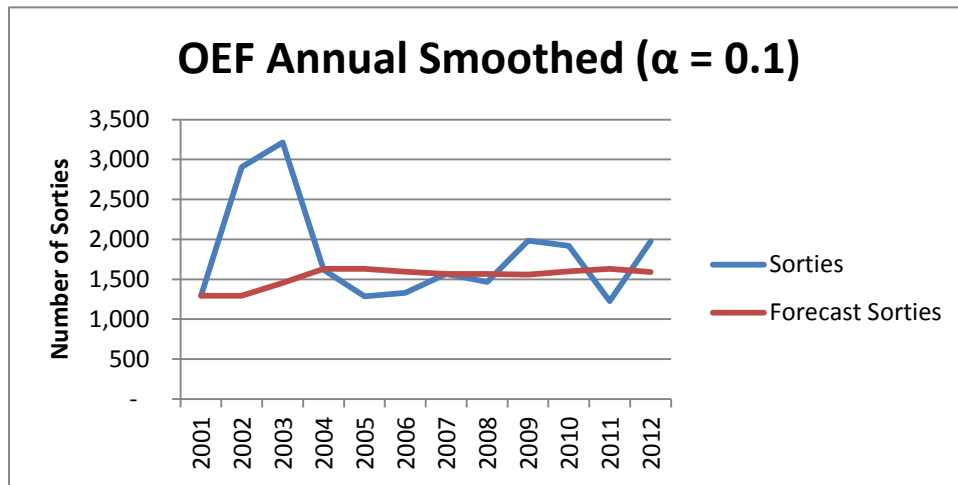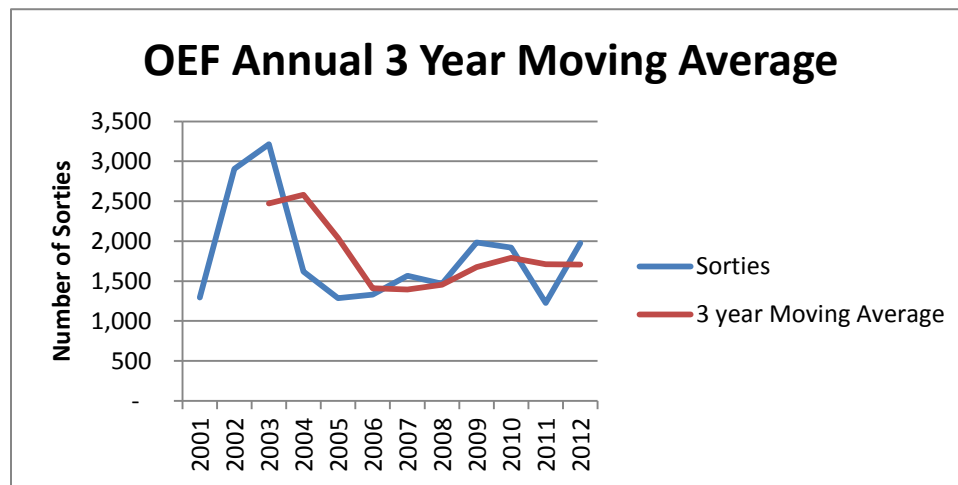**Figure 25: OEF Annual Data Smoothed ($\alpha = 0.1$)**

Figure 26: OEF Annual Data 3 Year Moving Average

TACC Data Set

Within the TACC data, the exponential smoothing forecast with an α of zero resulted in the minimum value for MAD of 954. The trend component did not improve the forecast, as the same MAD was achieved when α and β were zero. As in the OEF data set, the optimal values of zero for α and β suggest exponential smoothing is not an appropriate forecasting technique. The three year moving average forecast produces a MAD of 960. While not quantitatively superior to the exponential smoothing forecast, the moving average forecast incorporates historical information better than a horizontal line arbitrarily set at 7,400, the number of KC-135 sorties in 2005. Figure 27 depicts the moving average forecasts for TACC data.
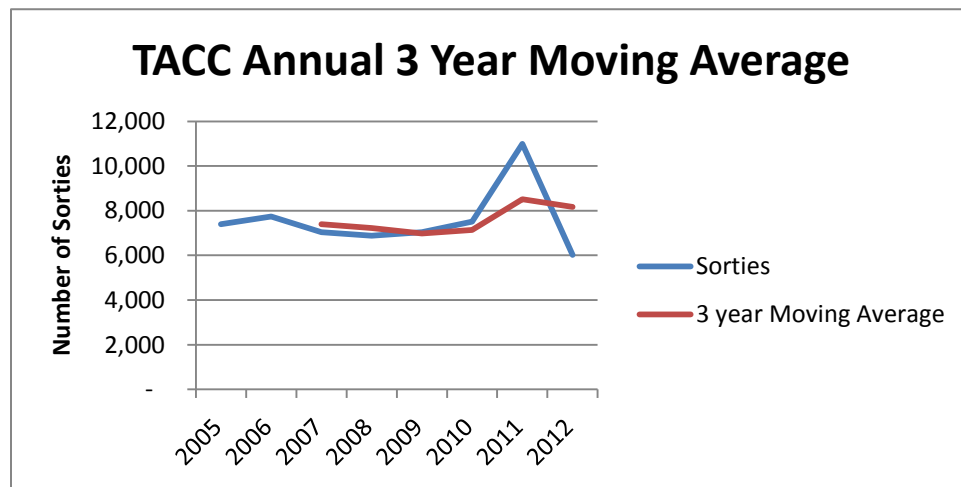
Figure 27: TACC Annual Data 3 Year Moving Average

Aggregate Data Set

Next, to apply the lessons learned from earlier analysis, this analysis aggregates the data from all three theaters into a single data set. The OIF and OEF data sets were adjusted to coincide with the start of the TACC data set in December 2004. Including

earlier data would skew the data, as the monthly sorties contributed by TACC could create a false trend. The minimum MAD for the simple exponential smoothing forecast was 887 at an α value of zero. The minimum MAD forecast for the exponential smoothing with trend adjustment forecast was also 887, at an α value of zero for all values of β. As with the individual data sets, this forecast was assessed to be of limited utility because of its inability to incorporate new information. The three year moving average forecast resulted in a MAD of 716. Figure 28 shows the moving average forecasts for the complete data set.
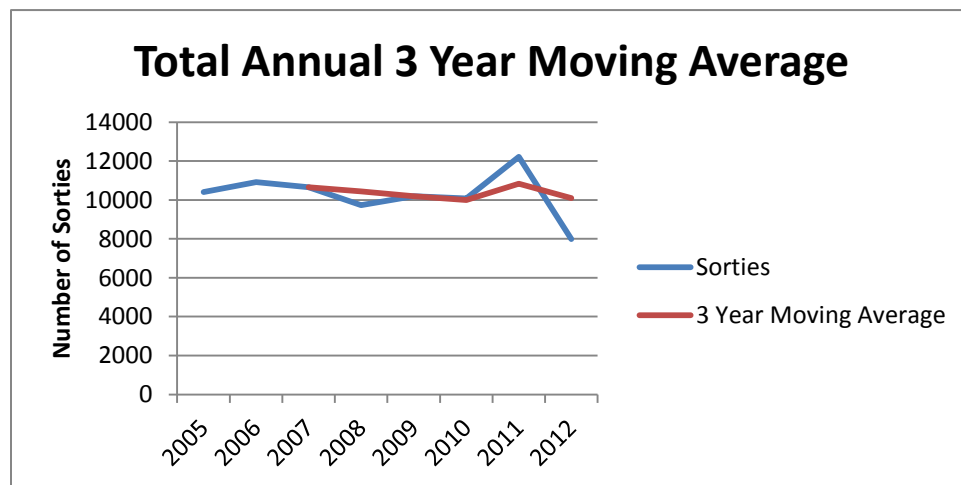
**Figure 28: Total Annual Data 3 Year Moving Average**

Time Series Regression

Finally, the analysis seeks trends in the data through a simple regression using time as the independent variable and the number of KC-135 sorties as the dependent variable. The constant in the regression equation is meaningless for the purposes of this research and will be ignored. The coefficient for the slope of the line indicates the

magnitude and direction of any trends present in the data. This coefficient will be the focus of this final analysis.

A linear regression of the total number of sorties resulted based on time period resulted in a coefficient of -138.5 sorties per year. However, standard error of the coefficient was calculated to be 190.3. Dividing the standard error by the coefficient results in a t statistic of -0.728. Based on a two tailed t-distribution with six degrees of freedom, this t statistic yields a p-value of 0.494. Because the magnitude of the standard error is greater than that of the coefficient, there are no statistically significant conclusions that can be drawn about the slope of the line. Figure 29 depicts KC-135 sorties by year with a linear regression trend line.
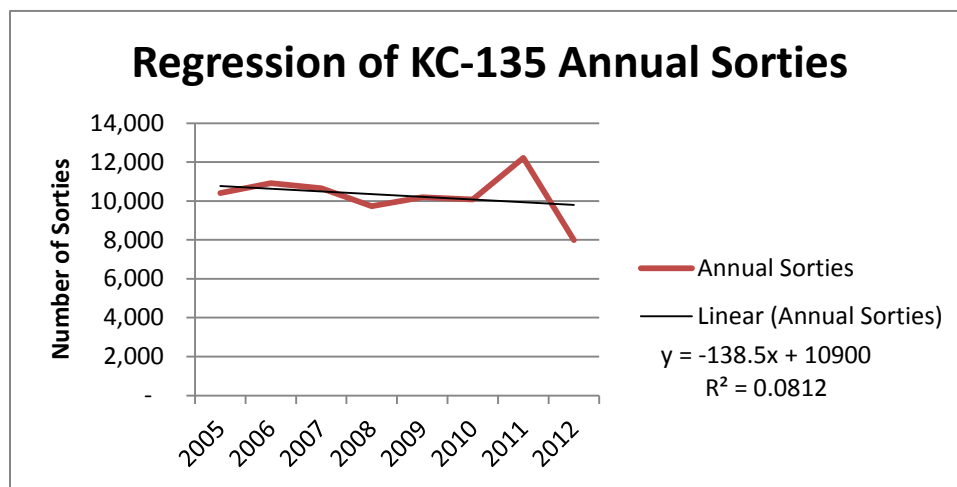
Figure 29: Linear Regression of KC-135 Sorties

Linear regression of the three year moving average of sorties resulted in a coefficient of   -67.738 sorties per year. Standard error of the coefficient was 44.722. This standard error resulted in a t statistic of -1.515, ultimately resulting in a p-value of 0.18. This p-value is not lower than 0.1, which is typically desired for strong statistical

significance. However, it is low enough to suggest the three year moving average of KC-135 sorties is declining. The R^2 value of 0.2766 emphasizes the fact that time is not the only variable impacting demand for KC-135 sorties. However, it does show some correlation. Figure 30 depicts the three year moving average of KC-135 sorties and the associated regression trend line.
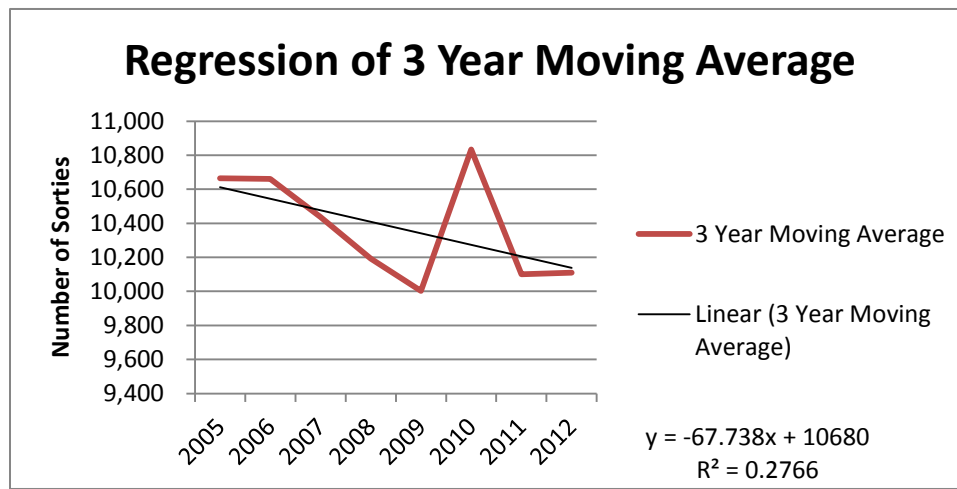
Figure 30: Linear Regression of 3 Year Moving Average of KC-135 Sorties

Investigative Questions Answered

The research was able to answer the following investigative questions posed in Chapter I:

- How many KC-135 air refueling sorties does AMC provide in support of CONUS fighter movements?

Based on the response from HQ AMC/A3RI, AMC does not provide a significant number of air refueling sorties in support of CONUS fighter movements. Since there are no sorties to consider, the second investigative question for Hypothesis 1 is irrelevant.

The KC-135 aircrew deploy to dwell ratio cannot be improved by eliminating this mission set as posed in Hypothesis 1.

- What trends exist in the number of KC-135 sorties flown as OIF drew to a close?

The OIF data indicates a steady decrease in KC-135 sorties for the last three years of operations in Iraq. However, the trend component of the forecast is only negative for the last two years. In either case, OIF KC-135 sortie data shows a downward slope for the final years, rather than level demand with an abrupt cessation.

- Can those trends be extrapolated to forecast demand for KC-135 sorties as operations in OEF draw to a close?

The steady decrease in KC-135 sorties observed in the OIF data could be applied to OEF data to forecast future demand in Afghanistan. However, the OIF analogy is not perfect. With the end of operations in Afghanistan projected for 2014, OEF data should indicate the beginnings of a downward trend. The lack of this decrease suggests the OIF analogy is not ideal.

- Was TACC utilization of KC-135 sorties affected by the end of OIF?

The overall demand for KC-135 sorties was unaffected by the end of operations in Iraq. While there was a sharp increase in TACC sorties in early 2011, the magnitude of the increase was several times that of the sorties no longer flown in Iraq. After the surge, TACC KC-135 sortie levels returned to pre-2010 levels. This suggests that TACC did not simply absorb the KC-135 sorties released by OIF. By analogy, the end of OEF should also provide relief for KC-135 aircrews.

50

- What trends exist in overall demand for KC-135 sorties?

A time series regression of the three year moving average of KC-135 sorties across all data sets indicates a downward trend of approximately 68 sorties per year. However, the p-value for this coefficient is only 0.18. While not ideal for rigorous statistical analysis, this suggests KC-135 sorties are indeed trending downward, which should improve the deploy to dwell ratio. Unfortunately, the relatively high p-value precludes a meaningful prediction of the magnitude of the change.

Based on the answers to the investigative questions uncovered above, this research estimates a slight improvement in the KC-135 aircrew deploy to dwell ratio, but short of AMC's goals. In a best case scenario, the same crew force that accomplishes approximately 8,000 sorties annually at a 1:1.3 deploy to dwell ratio could accomplish 6,000 sorties annually at a deploy to dwell ratio of approximately 1:1.7. This calculation assumes elimination of all OEF sorties, no increase in TACC tasked sorties, and similar average sortie durations between OEF and TACC. In reality, OEF sorties would likely not drop to zero, as some sorties would be required for CENTCOM OPLAN support. The TACC sortie assumption is supported by data analysis. Ultimately, AMC cannot attain their goal of a deploy to dwell ratio of 1:2 merely by waiting for the end of operations in Afghanistan.

Summary

This chapter discussed results of analysis performed to answer investigative questions tied to the research problem. With respect to Hypothesis 1, there is no

evidence to support the claim that AMC practices sub-optimal air refueling missions in support of CONUS fighter movements.

Data analysis provided more substantial results with respect to Hypothesis 2. Simple exponential smoothing proved to be the forecasting method which yielded the lowest MAD. Inclusion of a trend component never quantitatively improved the accuracy of the monthly forecast. This coincides with Maj DeYoung's analysis that exponential smoothing provides the best model for airlift demand forecasting (DeYoung, 2012:48). Forecasts using annual data suggest that demand for KC-135 sorties in both the TACC and OEF data sets is relatively constant. However, the three year moving average of all sorties has an arguably statistically significant downward trend, with a p-value of 0.18. However, this trend will not continue indefinitely. The OEF data set indicates approximately 1,800 sorties annually. The sorties "saved" in Afghanistan cannot exceed this amount. If the trends in the OIF data can be used as an analogy to forecast activity in Afghanistan, demand for KC-135 sorties in OEF data should begin a steady downward trend. However, this is not a perfect analogy. Figure 22 indicates the number of sorties in OIF began a steady downward trend three years before the conclusion of operations. From a quantitative perspective, sorties in the OEF data should have begun a decline already, rather than the relatively steady demand for sorties depicted in Figure 25. In the best case scenario, the KC-135 aircrew deploy to dwell ratio will improve to 1:1.7. AMC cannot achieve their goal of a 1:2 deploy to dwell ratio without taking action to increase the crew force or decrease the mission set.

V. Conclusions and Recommendations

Chapter Overview

The research accomplished thus far seeks to quantify trends in KC-135 sortie data in an attempt to forecast future demand for these sorties. The forecast represents an important element of the deploy to dwell ratio issue currently faced by AMC. This chapter includes a summary of conclusions from the data analysis, as well as the significance of the research. The chapter concludes with recommendations for further research.

Conclusions of Research

Data analysis does not support Hypothesis 1, that AMC can improve the deploy to dwell ratio of KC-135 aircrew members by reducing or eliminating KC-135 sorties flown in support of CONUS fighter movements.

Data analysis does support Hypothesis 2, that demand for KC-135 sorties is decreasing over time, which will result in a lower deploy to dwell ratio for KC-135 aircrew members, with some qualifications. Analysis of the three year moving average of all KC-135 sorties indicates a negative trend, albeit with a p-value of 0.18. The relatively high p-value precludes a quantitative conclusion on the speed at which demand will decrease. Analysis of individual data sets indicates a strong downward trend for the last three years of OIF data which will likely be analogous to future events in Afghanistan. However, this trend can only decrease demand for KC-135 sorties by approximately 2,000 sorties, the number currently being used by operations in that

53

theater. Additionally, the time frame of this decrease will not be directly analogous to events in Iraq.

Significance of Research

This research set out to quantify future demand for KC-135 sorties and possible avenues for reducing that demand. Time series demand forecasting is a prevalent topic in various industries, with existing research focusing primarily on commercial applications including tourism and air carriers. The limited amount of research on military applications of demand forecasting is further focused on air cargo applications. Existing research on air refueling deals principally with optimizing assignment of assets to requirements. While efficient use of resources is increasingly important in the current fiscal environment, understanding demand provides valuable insight into impending challenges. This research is significant in its use of forecasting techniques to predict demand for the air refueling subset of mobility operations.

Recommendations for Action

Hypothesis 1 states that AMC can improve the deploy to dwell ratio of KC-135 aircrew members by reducing or eliminating KC-135 sorties flow in support of CONUS fighter movements. However, data did not support the premise that TACC has a policy of supporting fighter movements within the CONUS with KC-135 air refueling sorties. This research supports a recommendation to continue the current policy and avoid CONUS fighter refueling except in cases of required tanker and receiver aircrew training.

Hypothesis 2 states that demand for KC-135 sorties is decreasing, which will result in a lower deploy to dwell ratio for KC-135 aircrew members. Quantitative time

series analysis of historical KC-135 sortie data from December 2004 to December 2012 indicates a negative trend in the number of sorties flown, but with a p-value of 0.18. This translates to a confidence level of only 82 percent. By combining the quantitative results with qualitative analysis tools including analogy to OIF and intervention to eliminate future OEF sorties, one could conclude that demand for KC-135 sorties will decrease in the coming years. By extension, the KC-135 aircrew deploy to dwell ratio will improve. Unfortunately, without a statistically significant coefficient on the sortie trend line, quantifying that decrease with confidence is impossible. In a best case scenario, eliminating all OEF sorties could result in a deploy to dwell ratio of approximately 1:1.7. AMC leadership must decide whether to accept this ratio, increase KC-135 manning, or decrease the KC-135 mission set.

Recommendations for Future Research

This research sought to quantify one aspect related to AMC's concern with the KC-135 aircrew deploy to dwell ratio. The literature review and ensuing research uncovered several areas where future research could provide additional insight on ways for AMC to focus its resources to address this challenging issue.

If AMC's KC-135 aircrew deploy to dwell issue were viewed in an economic framework, available aircrew would be analogous to supply, and the required mission set would equate to demand. This research focused on the mission set, attempting to quantify future changes to demand. One area for future research includes addressing the supply side of the relationship. Initially, this research attempted to quantify actual manning levels in order to identify constraining KC-135 aircrew positions by aircraft

commander, pilot, and boom operator. Unfortunately, a robust data set was not readily available on actual versus authorized manning levels. To provide the best analysis of the supply side of KC-135 aircrew deploy to dwell, this data should encompass actual manning levels at each wing. Important considerations include long term "duties not to include flying" (DNIF) status, whether the aircrew member is worldwide deployable, and level of mission readiness. While flying wings report a mission readiness metric that encompasses these considerations, a more granular data set could provide the basis for analysis indicating where AMC should focus its aircrew development resources.

In addition to understanding the overall supply of KC-135 aircrews, further research could address the impact of fundamental assumptions underlying KC-135 employment. Currently, AMC mans each KC-135 with approximately two current and qualified crews. On deployments, each KC-135 deploys with 1.5 crews. Each of these assumptions has a large impact on the deploy to dwell ratio. Further research could investigate whether AMC can reach deploy to dwell goals by adjusting these assumptions while maintaining the capability to meet combatant commander requirements.

An additional avenue for future research involves a similar analysis for all other mobility weapon systems. Although KC-135 aircrews currently have the worst deploy to dwell ratio, this analysis shows a decreasing trend in demand. A similar analysis for other aircraft in the mobility fleet could identify potential problems before they become critical. This information could inform AMC how best to prioritize its resources in training new aircrew members.

Future research could also attempt to quantify the impact of ARC volunteerism on deploy to dwell ratio, both in general and with respect to specific aircraft type. The

literature review reveals ARC volunteerism to be a multifaceted problem with critical impact on deploy to dwell ratios across the mobility fleet. A quantitative analysis of ARC volunteerism could consider the impact of variables including strength of the economy, duration of the commitment, and the enduring nature of the commitment. Additional research could determine the best way to incentivize the ARC to provide the crews necessary to reduce the active duty deploy to dwell ratio.

One assumption made when analyzing demand for KC-135 sorties was that all sorties should be weighted equally. However, this may not be the case. From personal experience, KC-135 sorties flown in support of OEF missions had longer average sortie durations than sorties flown in support of OIF. Average sortie durations for TACC tasked missions likely vary widely, as missions range from CONUS refueling to transatlantic and transpacific flights. Unfortunately, sortie duration data was unavailable. Further research could test the validity of this assumption by using hours flown to determine whether subsets of data should receive additional weight when forecasting future demand.

Another assumption for this research was that the number of KC-135 aircrews remains constant. However, as discussed in the literature review, high operations tempo and deploy to dwell ratios can encourage some aircrew members to choose alternatives to continued military service. Further research could address this assumption by analyzing retention rate of all aircrew members rather than focusing on just pilots. Additionally, research could analyze trends in aircrew retention for individual weapon systems to determine if the KC-135 or any other weapon system stands out with respect to retention issues.

Summary

    This research used time series forecasting techniques to identify trends in KC-135 sortie data. The analysis indicates a clear decreasing trend during the drawdown in Iraq. However, this trend is not directly analogous to operations in Afghanistan. The downward trend should be present based on a projected 2014 completion date, but no trend is evident in the data. Overall KC-135 sortie data shows a steady decrease in demand, but with a p-value of 0.18. In a best case scenario, the KC-135 aircrew deploy to dwell ratio will improve to 1:1.7 with the end of operations in Afghanistan.

Bibliography

6th Operations Support Squadron, Current Operations. Electronic mail. 7 January 2013.

Department of the Air Force. *Air Force Basic Doctrine, Organization, and Command*. Air Force Doctrine Document 1. Washington: HQ USAF, 14 October 2011.

Department of the Air Force. *Operations Planning: Air and Space Expeditionary Force*. Air Force Policy Directive 10-4. Washington: HQ USAF, 30 April 2009.

Deyoung, Daniel S. *Time Series Forecasting of Airlift Sustainment Cargo Demand*. Air Force Institute of Technology (AU), Wright-Patterson AFB OH, June 2012 (AFIT/IMO/ENS/12-05).

Eisen, Susan V., Mark R. Schultz, Dawne Vogt, Mark E. Glickman, A. Rani Elwy, Mari-Lynn Drainoni, Princess E. Osei-Bonsu, and James Martin. "Mental and Physical Health Status and Alcohol and Drug Use Following Return From Deployment to Iraq or Afghanistan," *American Journal of Public Health*, 102: S66-S73 (2012).

Fitzsimmons, James A. and Fitzsimmons, Mona J. *Service Management: Operations, Strategy, Information Technology* (7th Edition). New York: McGraw-Hill Irwin, 2011.

Headquarters Air Mobility Command A3/A3RI. Electronic mail. 3 January 2013.

Huscroft, Joseph R. *A Demand Side Requirements Model to Forecast C-17 Mobility Aircraft Availability*. Air Force Institute of Technology (AU), Wright-Patterson AFB OH, March 2004 (AFIT/GLM/ENS/04-06).

Johns, Raymond E., Commander, Air Mobility Command. "Mobility Aircraft Capabilities Assessment." Address to House Armed Services Subcommittee on Seapower and Expeditionary Forces. Washington, DC. 7 March 2012.

Kitfield, James. "Are We Wearing Out the Guard and Reserve?" *Air Force Magazine*, 84: 34-39 (February 2001).

Larkins, Alan. "Stress and the War on Error," *Mobility Forum: The Journal of the Air Mobility Command's Magazine*, 19: 4-7 (March-April 2010).

Nogales, F.J., J. Contreras, A.J. Conejo, and R. Espinola. "Forecasting Next-day Electricity Prices by Time Series Models," Power Systems, IEEE Transactions, 17: 342-348 (May 2002).

Polusny, Melissa A., Christopher R. Erbes, Paul A. Arbisi, Paul Thuras, Shannon M. Kehle, Michael Rath, Cora Courage, Madhavi K. Reddy, and Courtney Duffy. "Impact of Prior Operation Enduring Freedom/Operation Iraqi Freedom Combat Duty on Mental Health in a Predeployment Cohort of National Guard Soldiers," *Military Medicine*, 174: 353-357 (April 2009).

Wang, Chao-Hung. "Predicting Tourism Demand Using Fuzzy Time Series and Hybrid Grey Theory," *Tourism Management*, 25: 367-374 (June 2004).

Weatherford, L.R. and P.P. Belobaba. "Revenue Impacts of Fare Input and Demand Forecast Accuracy in Airline Yield Management," *The Journal of the Operational Research Society*, 53: 811-821 (Aug 2002).

Wicke, Russel. "AEF Evolves to Reflect Dwell-Ratios Stressed Career Fields." Online article. n. pag. (4 June 2008). http://www.lakenheath.af.mil/news/story.asp?id=123101322 Accessed 12 Nov 2012.

REPORT DOCUMENTATION PAGE

1. REPORT DATE *(DD-MM-YYYY)* 14-06-2013	**2. REPORT TYPE** Graduate Research Paper	**3. DATES COVERED** *(From – To)* 21-05-2012 – 14-06-2013

4. TITLE AND SUBTITLE

Forecasting Demand for KC-135 Sorties: Deploy to Dwell Impacts

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)

Langstroth IV, Theodore A, Maj

5d. PROJECT NUMBER
N/A

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAMES(S) AND ADDRESS(S)
Air Force Institute of Technology
Graduate School of Engineering and Management (AFIT/EN)
2950 Hobson Way, Building 640
WPAFB OH 45433-8865

8. PERFORMING ORGANIZATION REPORT NUMBER

AFIT-ENS-GRP-13-J-5

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
Mr. Donald Anderson, Assistant Director, AMC A9/AA9
1 Soldier Way Building 1900W, Room 1038
Scott Air Force Base, IL 62225-1604
(618) 220-7629 (DSN 770) donald.anderson.17@us.af.mil

10. SPONSOR/MONITOR'S ACRONYM(S)
AMC A9/AA9

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT

Distribution Statement A. Approved for public release; distribution is unlimited.

13. SUPPLEMENTARY NOTES

14. ABSTRACT

The KC-135 aircrew deploy to dwell ratio is currently 1:1.3, well above the Air Mobility Command goal of 1:3. On average, a KC-135 aircrew member is away from home station nearly six months of every year. While undoubtedly a quality of life issue, the deploy to dwell ratio may be an indicator of more serious problems. Research indicates sustained high operations tempo can have a negative impact on flying safety, aircrew retention, and even physical or mental health. This research applies time series forecasting techniques to KC-135 sortie data from operations in Iraq, Afghanistan, and CONUS missions. These forecasts identify trends for use in predicting future changes to the deploy to dwell ratio. Data from the Iraq drawdown are used to develop an analogy for a similar drawdown in Afghanistan projected for 2014. Aggregate data are analyzed for overall trends. The three year moving average of KC-135 sorties indicates a downward trend in sortie demand, but with marginal statistical confidence. The analysis suggests the KC-135 deploy to dwell ratio will improve, but does not positively quantify that improvement. In a best case scenario, active duty KC-135 aircrew deploy to dwell ratio could improve to 1:1.7 with the end of OEF.

15. SUBJECT TERMS
Deploy to Dwell ratio; Air Refueling Demand Forecasting; KC-135; Time Series Demand Forecasting

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON** Lt Col Bradley E. Anderson, Ph.D (AFIT/ENS)
a. REPORT U	**b. ABSTRACT** U	**c. THIS PAGE** U	UU	72	**19b. TELEPHONE NUMBER** *(Include area code)* (937) 255-3636, x 4538 bradley.anderson@afit.edu